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Issue Article

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ANALYSIS OF THE APPLICATION OF OPTIMIZATION ALGORITHMS FOR TEMPERATURE REGIME CONFIGURATION OF VEGMAN SERVERS

Abstract: *The article is devoted to optimization algorithms for selecting the coefficients of the PID controller of system fans. Based on programs developed in python, the effectiveness of using various algorithms to adjust the temperature regime of servers is considered. To achieve this aim, the following tasks were addressed:*

– meta-heuristic optimization algorithms were studied, including particle-swarm optimization, ant-colony optimization, Bayesian optimization, and the genetic algorithm;

– a Python program implementing these algorithms was developed;

– a comparative analysis of the algorithms was carried out, and the one most effective by the combined criteria was selected (lowest post-tuning oscillation amplitude, shortest tuning time, fastest convergence to the target temperature, minimal fan speed).

As a result, an optimal algorithm was selected that can effectively find PID controller coefficients that ensure a stable processor temperature at the minimum required fan speed.

Key words: *VEGMAN servers, meta-heuristic optimization algorithms, PID-coefficients, experiment, metrics, frameworks.*

Language: *English*

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Introduction

Today servers are employed everywhere – from small businesses to industrial complexes and government agencies. Any organisation that needs services such as:

– remote connection to the corporate network from multiple accounts;

– organisation and structuring of data and working documents with 24/7 access;

– backup and data storage, requires its own server.

VEGMAN servers (Figure 1) are high-performance computing systems manufactured by the Russian company YADRO [1].

Fig 1. External view of one of the VEGMAN servers

Key application areas for these servers include:
– hosting employees' workplaces on a local or cloud server rather than on individual PCs;
– data storage and management across a cluster of server nodes;
– high-performance computing systems;
– big-data analytics;
– machine learning and artificial intelligence.

The VEGMAN product line is built on 3rd-generation Intel Xeon Scalable Processors. The servers support up to 32 cores, processor cache sizes up to 36 MB, and an accelerated UPI bus of 11.2 GT/s. They can accommodate up to 8 TB (32×256 GB) of RAM.

An improved chassis design simplifies maintenance and operation. The entire VEGMAN range is compatible with YADRO's integrated solution for centralised infrastructure management and monitoring.

Servers operate continuously, executing resource-intensive tasks and therefore generating significant heat. If this heat is not controlled, serious issues may arise, such as:
– overheating of the CPU;
– unstable operation of RAM;
– failures of hard drives and other components;
– loss of critical data;
– service downtime.

To prevent such problems, servers are equipped with high-performance fans that create an intensive airflow inside the chassis and efficiently remove heat from the hottest components. Modern server-grade fans can run at various speeds, depending on the current system load. Higher fan speeds provide better cooling but at the cost of increased noise, greater vibration on fan bearings and higher power consumption.

Thus, reliable and efficient server operation demands a fan-control strategy that keeps temperature, rotational speed and power draw at optimal levels.

Proportional–Integral–Derivative (PID) controllers are the most widespread solution; they are used in roughly 90–95 % of control loops because their compact and simple structure achieves the control target for most technological objects. Tuning a fan PID controller is reduced to selecting three coefficient values. Incorrect tuning can lead to system overheating or unnecessarily high fan speeds, accompanied by elevated power usage and noise.

The traditional solution is a built-in PID controller that adjusts fan speed according to sensor temperatures. Such controllers maintain the specified component temperatures (CPU, GPU, motherboard, etc.) by increasing fan RPM as temperatures rise, attempting to keep them within an allowable range. The drawback of this approach is the need to tailor the coefficients to a specific configuration (number of fans, component heat output, sensor characteristics). Manufacturers usually perform this tuning during development, but real-world operating conditions may differ (e.g. higher ambient temperature, dust accumulation, partial fan failure), leading either to excessive fan noise and energy consumption or to unsafe operating modes.

Consequently, developing software methods for automatically selecting optimal PID-controller coefficients for server cooling systems is a relevant and important task.

Problem Statement

Thus, a server's cooling system is implemented with fan-based PID controllers, while the controller's PID coefficients are tuned by a program that runs optimization algorithms.

The goal is to select an efficient optimization algorithm. The algorithm should provide selection of PID controller coefficients that maintain a stable server temperature and provide the minimum required fan speed.

Algorithms for PID-Coefficient Tuning
The Concept of PID Control

A Proportional–Integral–Derivative Controller is a mechanism used in closed-loop control systems to keep a specified variable at a desired level automatically. It adjusts a time-varying parameter by computing a control signal that is the sum of three terms—each based on the difference between the set-point and the feedback signal: proportional, integral, derivative.

PID controllers belong to the class of continuous-action devices and are by far the most common solution in automatic-control systems. They respond rapidly, take the trend of the error into account and are robust to noise [2].

The first PID controllers appeared in the early 20th century. E.Sperry used a prototype autopilot with PID-like behaviour for a ship in 1911, and in 1922 N.Minorsky published the first theoretical paper on PID control, showing that adding a derivative term greatly improves heading accuracy.

The block diagram of a PID controller is shown in Figure 2. The controller operates in a closed loop with negative feedback. The set-point and the measured process variable (feedback) enter the controller, which computes the error $e(t)$ as their difference and generates a control action $u(t)$ aimed at minimising that error.

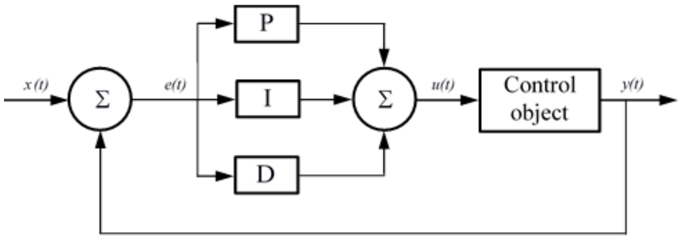

Fig 2. Block diagram of a PID controller

The country's leadership set the goal of educating physicists in the rather harsh conditions of that time who would be able to conduct research at a "world level".

A real plant – e.g. a server chassis with cooling fans – exhibits inertia and time delay, so purely proportional action leads either to a steady-state error or to oscillations. The integral term removes the steady-state error, while the derivative term damps the oscillations.

Mathematical Model of a PID Controller

$$u(t) = P + I + D = K_p e(t) + K_i \int_0^{\tau} e(t)dt + K_d \frac{de(t)}{dt}$$

where $u(t)$ – control signal; P – proportional component; I – integral component; D – derivative component; $e(t)$ – error (difference between set-point and measurement); Kp – proportional gain; Ki – integral gain; Kd – derivative gain.

PID-Controller tuning [3] consists in selecting the three gains (proportional, integral and derivative) so that the controller keeps the controlled variable within an acceptable range around its set-point.

Increasing Kp raises the speed at which the process reaches its set-point. Raising Ki accelerates compensation of the accumulated error, enabling the system to converge on the set-point over time. Increasing Kd prevents the system from changing too quickly.

Hence, a PID controller can drive a plant to its reference value both rapidly and accurately, reducing the steady-state error and the oscillatory nature of the transient response. A transient response is the process whereby the system moves from one steady operating mode to another.

To assess closed-loop control quality, the performance indices of the transient response shown in Figure 3 are used: regulation time, steady-state value, overshoot and steady-state error.

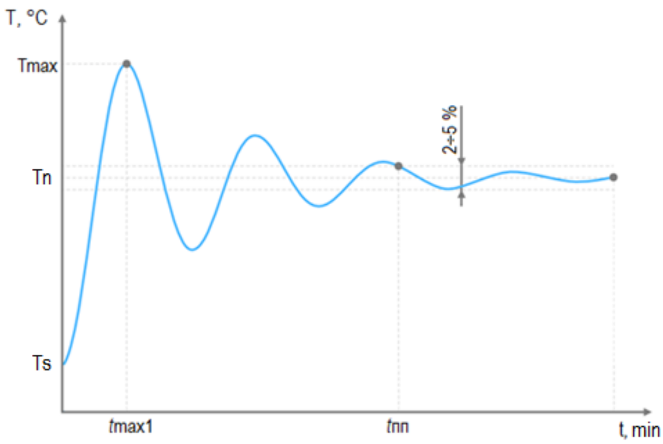

Fig 3. Example of a transient-response plot

Regulation time – the interval from the start of a mode change until the system settles in a new steady state, where the controlled variable remains within ±5% of its steady-state value (Tn ±5%).

Steady-state value – the value of the controlled variable after the system has settled.

Overshoot – the maximum deviation of the controlled variable, expressed as a percentage of its steady-state value, in the direction opposite to the initial deviation.

Steady-state error – the difference between the desired value of the controlled parameter and its actual value in the steady state. An ideal transient response has zero steady-state error.

The usual tuning goal is to obtain the shortest possible regulation time while keeping overshoot below a specified limit.

If the controller reaches the set-point with a steady-state error, an integral term is added. When tuning the derivative gain, one must strike a compromise between transient-response quality and sensitivity to noise.

The primary function of server fans is to keep the system temperature within permissible limits. Optimally tuning a server fan means selecting PID coefficients so that the temperature-oscillation curve approaches the "ideal curve" shown in Figure 4.

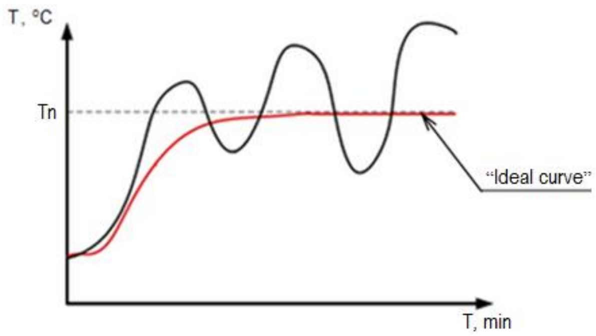

Fig 4. Temperature curve for PID-coefficient tuning

Classical manual tuning of PID controllers often requires further fine-adjustment and remains a labour-intensive process. Nowadays, automatic selection of PID coefficients according to predefined quality criteria – e.g. minimal transient time, minimal deviation from the set-point, or the best overall objective value – is increasingly employed. To solve this task, intelligent-optimization and machine-learning methods are used; they explore the PID-coefficient search space and identify the best solution.

The remainder of this section examines temperature-control of servers via fan-PID-coefficient tuning with modern optimisation algorithms.

Optimisation Algorithms

Optimisation algorithms are computational methods employed to find, within a set of feasible solutions, the best possible one for a given problem. In practice, multiple constraints must usually be taken into account when searching for the optimum.

Algorithmic optimisation reduces run-time and memory consumption and improves system scalability, thereby making software more efficient.

One distinguishes between tasks of static optimization: for processes in steady operating modes, and dynamic optimisation. Static optimisation addresses creation and implementation of an optimal model of the process, whereas dynamic optimisation concerns creation and implementation of an optimal-control system under non-steady operating conditions [4].

When solving optimisation problems, one must choose control parameters, such as temperature or time and impose limits on them.

Approaches are commonly divided into two categories:

– exact methods, which include brute-force enumeration, dynamic programming and the branch-and-bound method;

– approximate (meta-heuristic) methods.

In practice, exact methods, especially brute force, prove extremely laborious. A reduced enumeration, based largely on dynamic programming and step-by-step improvement of solutions, is therefore frequently adopted.

For multi-parameter objective functions, meta-heuristic methods (genetic and ant-colony algorithms, particle-swarm optimisation, etc.) deliver the greatest efficiency. Their key advantage lies in stochasticity: they can successfully solve complex problems without prior knowledge of the search-space structure. Moreover, when well implemented, meta-heuristics can find optimal or near-optimal solutions within a reasonable number of iterations [5].

In simplified terms, meta-heuristics may be viewed as algorithms that perform a directed random search for feasible solutions (optimal or close to optimal) until a stopping criterion is met or a preset iteration limit is reached [6].

Impact Factor:	ISRA (India) = 6.317	SIS (USA) = 0.912	ICV (Poland) = 6.630
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	JIF = 1.500	SJIF (Morocco) = 7.184	OAJI (USA) = 0.350

Particle-Swarm Optimisation

The particle-swarm optimisation (PSO) algorithm, developed by James Kennedy and Russell Eberhart in 1995 [7], is designed to locate the global extremum of complex multi-parameter functions. The idea was inspired by studies of collective behaviour in fish schools, bird flocks, and similar groups. Just as birds adaptively change direction, particles adjust their trajectories on the basis of personal experience and a group norm (the global optimum), collectively producing the overall search behaviour.

PSO is a meta-heuristic algorithm and serves as a method for optimising non-linear functions. A block diagram of the particle-swarm algorithm is shown in Figure 5.

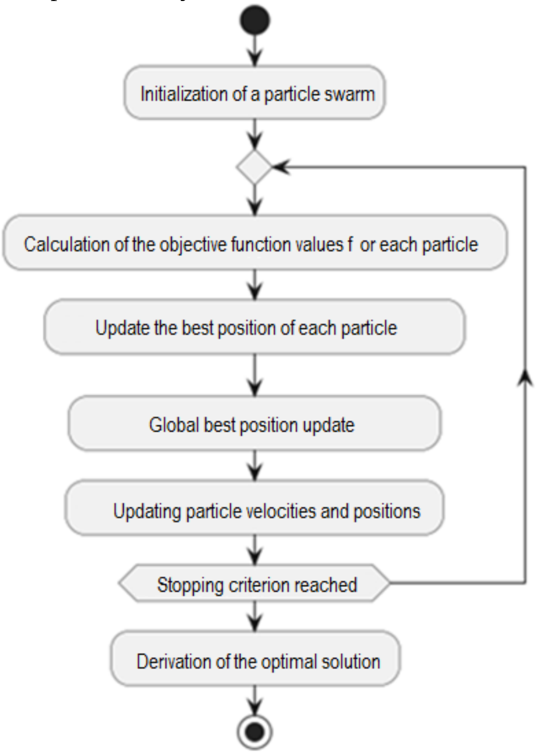

Fig.5 Block diagram of the particle-swarm optimisation algorithm

Particles move within the search space. Initially, they are randomly scattered over the entire domain. Each particle's current state is defined by its velocity vector $\boldsymbol{v}_i^t$ and its position $\boldsymbol{x}_i^t$.

The objective-function value is evaluated at every point a particle visits. Each particle stores the best objective value (best position) it has found so far and is also aware of the globally best position discovered by the swarm.

At each iteration, particles adjust their motion (both speed and direction) on the basis of the particle's own best solution and the swarm's best solution.

The update rule is:

$$\vec{v}_i^{t+1} = w\vec{v}_i^t + c_1 r_1^t\left(\vec{p}_i - \vec{x}_i^t\right) + c_2 r_2^t\left(\vec{g} - \vec{x}_i^t\right),$$

where $\vec{\boldsymbol{v}}_i$ – velocity of particle *i*; $\vec{\boldsymbol{x}}_i$ – position of particle *i*; *w* – inertia weight, responsible for preserving the current direction of motion and accelerating convergence [8]; $\vec{\boldsymbol{p}}_i$ – best position found by particle *i*; $\vec{\boldsymbol{g}}$ – global best position found by all particles; c_1 – cognitive-component coefficient, reflecting the influence of the particle's own experience; c_2 – social-component coefficient, reflecting the influence of the swarm; r_1, r_2 – stochastic weights, ~ U(0, 1).

After a number of iterations, particles concentrate near the most promising regions. The process repeats until a stopping criterion is met—for example, a preset number of iterations or a required solution quality.

The particle-swarm algorithm remains one of the simplest yet most effective methods of global optimisation. Its power lies in the minimalism of the model and the flexibility that allows it to be adapted to continuous, discrete and multi-objective problems.

Advantages:

– Easy to program and does not require gradient information on the objective function.

– Efficient on continuous, high-dimensional problems: it attains a solution faster than, or comparable to, genetic algorithms, but with fewer iterations thanks to the use of knowledge about the best positions.

– Capable of global search.

– Scalability and parallelism: fitness evaluation of particles is independent, so computations can be effectively parallelised for large swarms.

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Ant-Colony Algorithm

Ant-colony optimisation (ACO) was introduced by Marco Dorigo in 1992 [9]. The method mimics the behaviour of ants that lay down paths while foraging. Ants explore the solution space and mark successful trajectories with pheromone, which guides other ants toward more advantageous routes. Pheromone concentration is updated at every iteration; over time the pheromone evaporates, preventing premature convergence.

The ant-colony algorithm is a particular instance of swarm intelligence [10], in which collective behaviour emerges without centralised control. A solution is constructed step by step on the basis of purely local information.

Thanks to several enhancements – such as pheromone evaporation [11] and stochastic decision making – the method has proved effective for many combinatorial-optimisation tasks. ACO has become a distinct research direction that has spawned numerous variants [12]. It is applied to discrete and partially continuous optimisation problems, including routing, planning and scheduling, clustering, and similar tasks where an optimal or near-optimal combination must be found.

Unlike particle-swarm and genetic algorithms, the ant-colony algorithm builds solutions by progressively selecting discrete elements.

The algorithm can be illustrated by the problem of finding the shortest path between two vertices of a graph $\boldsymbol{G}=(\boldsymbol{V}, \boldsymbol{E})$, where $\boldsymbol{V}$ is the vertex set and $\boldsymbol{E}$ is the edge-incidence matrix.

Let $\boldsymbol{n_G}=|\boldsymbol{V}|$ – the number of vertices, $\boldsymbol{L^k}$ – denote the length (number of edges) of the path constructed by the $\boldsymbol{k}$-th ant. Every edge $\boldsymbol{i}, \boldsymbol{j}$ initially carries the same pheromone level τ_{ij}, which is updated at each algorithm iteration [13].

An example of a graph is shown in the Figure 6.

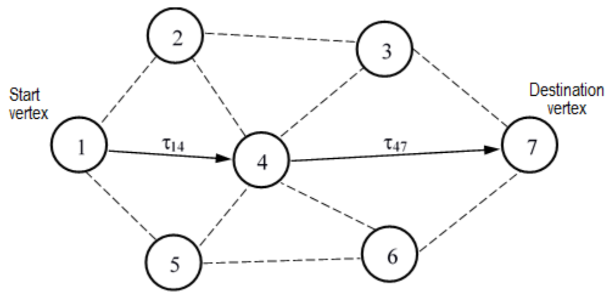

Fig.6 Example of a graph

A colony of $\boldsymbol{k}=\{1, \dots n_k\}$ ants is placed on the start vertex. During each iteration every ant step-by-step builds a path to the destination vertex. When the $\boldsymbol{k}$-th ant is at vertex $\boldsymbol{i}$, it selects its next vertex $\boldsymbol{j} \in \boldsymbol{N_i^k}$ according to the transition probabilities:

$$p_{ij}^k = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{l \in available} \tau_{il}^{\alpha} \cdot \eta_{il}^{\beta}}$$

where $\boldsymbol{N_i^k}$ – set of feasible successor vertices for $\boldsymbol{k}$-th ant at vertex $\boldsymbol{i}$; $\boldsymbol{p_{ij}^k}$ – probability that ant $\boldsymbol{k}$ moves along edge $\boldsymbol{i} \to \boldsymbol{j}$; $\boldsymbol{\tau_{ij}}$ – pheromone level on edge $\boldsymbol{i} \to \boldsymbol{j}$; $\boldsymbol{\eta_{ij}}$ – heuristic information, e.g. inverse edge length, $\boldsymbol{\eta_{ij}} = \boldsymbol{1/d_{ij}}$; $\boldsymbol{\alpha}$ – pheromone weight (large $\boldsymbol{\alpha}$ makes ants rely strongly on current pheromone and can cause premature convergence); $\boldsymbol{\beta}$ – heuristic weight.

If $\boldsymbol{N_i^k} = \emptyset$, for some vertex $\boldsymbol{i}$ and $\boldsymbol{k}$-th ant, the predecessor of $\boldsymbol{i}$ is re-inserted into $\boldsymbol{N_i^k}$; loops may thus appear and are removed once the ant completes its path.

After all ants have finished, each ant deposits pheromone on every edge of its path in proportion to path quality:

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L^k}, j \in N_i^k \text{ (if } \boldsymbol{k} - \text{th ant walked along the edge } \boldsymbol{i} \to \boldsymbol{j}) \\ 0, \mathrm{j} \notin N_i^k \end{cases},$$

where $\Delta\boldsymbol{\tau_{ij}^k}$ – pheromone level on edge $\boldsymbol{i} \to \boldsymbol{j}$ from the $\boldsymbol{k}$-th ant; $\boldsymbol{L^k}$ – the path length of $\boldsymbol{k}$-th ant; $\boldsymbol{Q}$ – constant that determines the amount of pheromone from the $\boldsymbol{k}$-th ant.

Global pheromone update for each edge is:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \sum_{k=1}^{n_k} \Delta\tau_{ij}^k(t)$$

where $\boldsymbol{n_k}$ – number of ants; $\boldsymbol{\rho}$ – the pheromone-evaporation coefficient.

The total pheromone on an edge is proportional to the quality of the paths containing that edge; here quality is inversely proportional to path length, though other metrics (e.g. geometric distance) can be used.

Let $\boldsymbol{x^k(t)}$ be the solution found by $\boldsymbol{k}$-th ant at iteration $\boldsymbol{t}$ when $\boldsymbol{f(x^k(t))}$ its quality. If $\Delta\boldsymbol{\tau^k}$ is independent of quality – i.e. every ant deposits the same amount of pheromone – edge choice depends solely on path length. This yields two main evaluation schemes used in ACO: implicit evaluation – ants rely only on path-length differences; explicit evaluation – deposited pheromone is proportional to an explicit quality measure.

Typical termination criteria [14]: a preset maximum number of iterations; an acceptable solution quality, $\boldsymbol{f}(\boldsymbol{x}^k(\boldsymbol{t})) \leq \varepsilon$; all ants following the same path.

Strengths algorithm:

– global-search capability and resistance to local traps, especially when pheromone evaporation is used [15];

– adaptive learning: through pheromone memory the algorithm progressively focuses on promising regions, effectively learning from earlier agents and enabling exploration of large search spaces;

– flexibility: by tuning the pheromone-update scheme one can influence algorithm behaviour.

Weaknesses algorithm:

– slow convergence: many iterations are usually required before high pheromone concentration accumulates on the optimum;

– parameter sensitivity: careful adjustment of deposition intensity and evaporation rate is needed [16];

– memory demand: storing and updating the pheromone matrix can be costly.

In relation to the selection of PID coefficients, each graph node represents a combination of PID coefficients. The quality of the system operation with the current coefficients (settling time, overshoot) is assessed. After each iteration, the coefficients are updated, and the system is tested in real time.

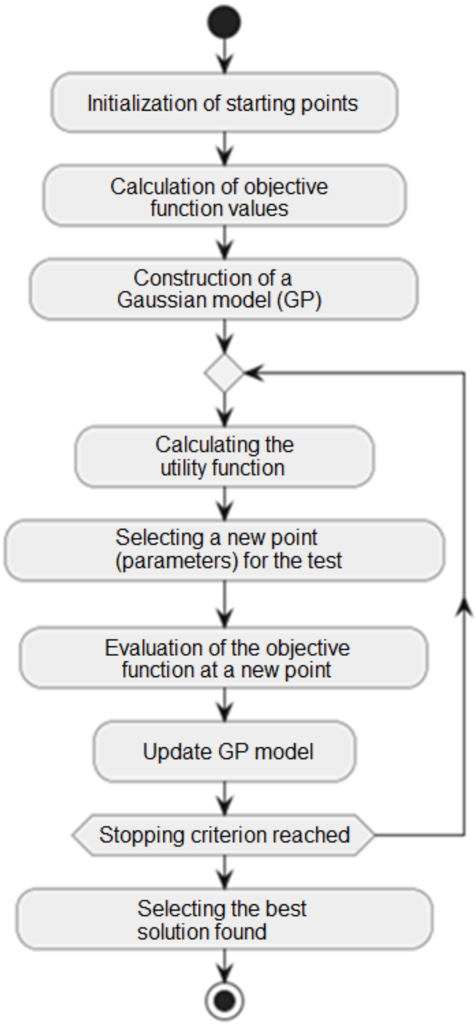

Fig.7 Block diagram of the Bayesian-optimisation procedure

Bayesian Optimisation

Bayesian optimisation is a search method that relies on a probabilistic surrogate model – most often a Gaussian process – and on the purposeful selection of new evaluation points guided by that model.

The idea was outlined in statistical-optimisation work as early as the 1970s, but the method gained widespread popularity in the 2010s thanks to its success in automatically tuning the hyper-parameters of machine-learning models [17].

Bayesian optimisation is intended for functions whose gradients are unavailable or expensive to compute, and it is particularly effective when only a small number of function evaluations is permissible. The Gaussian process approximates the objective function, predicting its value at unseen points while also providing the prediction variance – that is, the model's uncertainty.

The execution order of Bayesian optimization is shown in Figure 7.

The key idea is to build and continuously update a probabilistic model of the objective function, which then steers the search for the optimum.

At the initial stage, a set of starting points is selected from the space of possible solutions, at which the values of the objective function are calculated. Based on the results obtained, an initial model (Gaussian process) is formed, which estimates not only the approximate value of the function at unexplored points, but also the uncertainty of this estimate.

Then, at each iteration, the algorithm computes a utility function, such as the expected improvement relative to the current best observed value. The maximum of the utility function indicates the next point in the parameter space to explore. The probabilistic model is updated based on the new observation. These steps are repeated until a stopping criterion is met, such as a specified number of iterations, or until the improvements become insignificant.

Let S_t set of previous observations of the objective function $\boldsymbol{f}$: ($\boldsymbol{f}(\boldsymbol{x}_1)$, ...,$\boldsymbol{f}(\boldsymbol{x}_t)$), α – a function that determines the strategy for choosing the next point. Then:

– point selection: $x_{t+1} = \arg max_{x \in X} \alpha(x|S_t)$;

– evaluation and data augmentation: $\boldsymbol{S}_{t+1}=(\boldsymbol{S}_t, \boldsymbol{f}(\boldsymbol{x}_{t+1}))$;

– model update – refit (or incrementally update) the GP with the enlarged data set.

For efficiency, α should be differentiable and inexpensive to compute.

Advantages;

– highly sample-efficient: finds good optima with far fewer evaluations than model-free methods;

– provides principled guidance on where to sample next – the GP yields both a prediction and a confidence interval;

– guarantees monotonic improvement in expectation: the acquisition balances exploration (high uncertainty) and exploitation (high predicted value);

– adapts to many function classes, from smooth to discontinuous;

– largely automatic: alternates exploration/exploitation without manual intervention [18].

Limitations:

– performance degrades if the true function is poorly approximated by the chosen surrogate;

– scalability: GP have cubic complexity in the number of points, which limits the number of iterations;

– no absolute guarantee of locating the global optimum; the search may stagnate near a local optimum of the acquisition function;

– implementation complexity: requires choices of GP prior, acquisition form, data normalisation, etc. – though several mature libraries exist.

The chief benefit of Bayesian optimisation is its efficiency when experiments are costly – crucial for tuning a server's thermal regime, where each test run (CPU stress, controlled heating) is time-consuming and stresses hardware. Drawbacks include the computational overhead of maintaining the statistical model as data accumulate and the comparative coding complexity. Nevertheless, with only three parameters (the PID gains) and a moderate iteration budget, Bayesian optimisation is well suited to this problem.

In this application the GP surrogate approximates a quality-of-control objective (e.g. settling time, overshoot). At each iteration a new set of PID gains is selected, applied to the live system, and the resulting performance is fed back into the model.

Genetic Algorithm

The genetic algorithm (GA) is one of the oldest and best-known evolutionary optimisation methods. Its development is associated with the work of John Holland in the 1960s–70s; the concept was formalised in his 1975 book Adaptation in Natural and Artificial Systems [19].

A genetic algorithm is a heuristic search technique based on the processes of selection, mutation and recombination (crossover). Solutions are modelled as chromosomes that undergo crossover, mutation and selection in analogy with biological evolution. These mechanisms enable the GA to explore complex search spaces efficiently and to locate good – often optimal – solutions in situations where classical methods may become trapped in local optima.

The GA can handle problems with both discrete and continuous variables, including PID-coefficient tuning.

A classical GA operates on a population $\boldsymbol{P}$ of $\boldsymbol{N}$ individuals. Each individual possesses a chromosome $\boldsymbol{X}$ and a corresponding objective-function value, which plays the key role during selection. Only the best individuals are chosen to create the next generation.

The block diagram of the algorithm is shown in Figure 8.

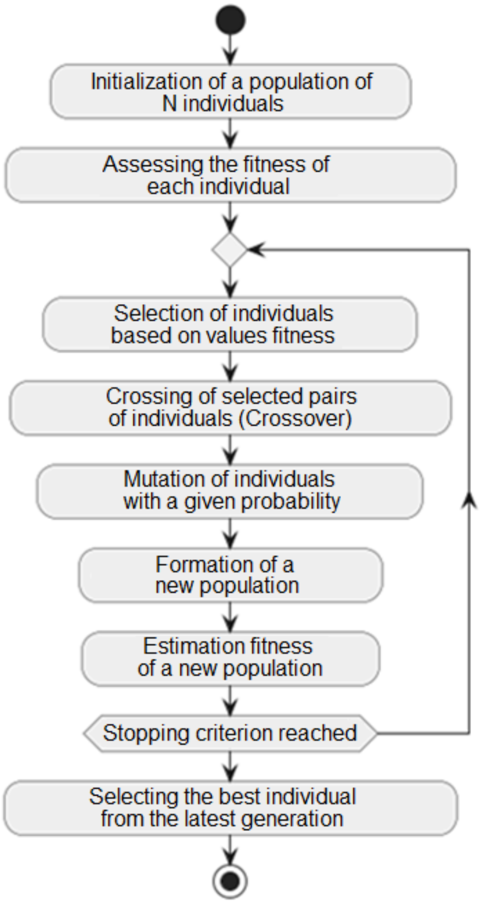

Fig.8 Genetic Algorithm flowchart

A starting population ***P*** is created by assigning each individual ***N*** a random parameter value ***X*** within the permissible range.

*Note – Initialisation may be controlled: for part of the population **X** is generated at random, while for another part it is produced heuristically or derived from previous solutions.*

After initialisation, the ***fitness*** value ***X*** is calculated for every individual.

Then, until a stopping criterion is met (e.g. maximum generations, attainment of a target objective value, or stagnation), the following cycle is repeated:

– selection: parents are chosen with probabilities proportional to their fitness;

– crossover: with probability ***Pc*** each parent pair exchanges genetic material to create offspring that combine desirable traits;

– mutation: a subset of individuals undergoes random gene mutations with probability ***Pm***;

– replacement: a new population ***P′*** is formed from the offspring and, if required, from the best parents (elitism);

– evaluation: fitness is computed for every individual in ***P′***;

– formation of the next generation: the most fit individuals from the union of parents and offspring are retained, thereby regulating population size. On average, each new generation displays higher fitness than its predecessor.

Note – A new generation may replace the old one entirely or only partially.

Advantages:

– simplicity and wide applicability: usable for any problem in which a solution can be encoded and its quality evaluated; no assumptions about smoothness or convexity are needed;

– global stochastic search: a population explores many regions in parallel; even if some individuals fall into local minima, others may find alternative routes, increasing the chance of reaching the global optimum compared with gradient-based methods;

– robust to multiple local extrema, discontinuities and noise: mutation and recombination help cross local barriers, while selection drives the search toward better regions;

– natural parallelism: fitness evaluation is independent across individuals, enabling acceleration on multi-core or distributed systems;

– configurable behaviour: by adjusting population size, mutation rate and selection strategy one can favour either fast, coarse search or slow, thorough exploration.

Drawbacks:

– slow convergence: usually requires many objective-function evaluations – fewer than exhaustive search but often more than specialised methods that exploit gradients or problem structure;

– parameter sensitivity: careful tuning of mutation rate, preservation of diversity, etc. is necessary to prevent the population from collapsing prematurely around sub-optimal solutions;

– lack of universal settings: population size and mutation probability typically must be chosen empirically for each task;

– no guarantee of optimality: like other heuristics, a GA cannot prove global optimality and should be viewed as a means of finding an acceptable solution.

The GA's great flexibility is simultaneously an advantage – broad applicability – and a disadvantage, because it does not exploit problem-specific structure and may run more slowly than dedicated algorithms.

A GA population is created in which every individual encodes one triple of PID gains. The control quality (fitness function based on minimising temperature-regulation error) is measured for the current coefficients; after each iteration the coefficients are updated and the system is tested in real time.

Results

Testing Results

All algorithms were executed automatically via the YADRO Kiwi system.

The efficiency of the different algorithms for selecting PID-controller gains for VEGMAN fan control is summarised in Table 1.

Table 1 – Comparison of optimisation algorithms for PID-coefficient tuning on VEGMAN servers

Metric / Indicator	Particle-Swarm Method	Ant-Colony Algorithm	Bayesian Optimisation	Genetic Algorithm
Maximum fan speed, rpm	12100	11700	11500	12000
RMS deviation of CPU temperature, °C	0,99	0,96	0,95	1,02
Number of iterations	5	6	14	5
Stabilisation time, s	900	550	350	800
Total algorithm run-time, s	6000	9900	4200	7200

From the comparison it is clear that Bayesian optimisation achieves the best control quality – minimum temperature overshoot and the fastest stabilization – while requiring the fewest iterations. Particle-swarm optimisation (PSO) also delivers high quality and short settling time, but at the cost of more iterations. The genetic algorithm (GA) produces an acceptable result, yet needs still more iterations to reach a quality close to that of PSO. The ant-colony algorithm (ACO) shows the weakest dynamics: its overshoot is higher and the transient process longer, indicating less accurate PID tuning and slower convergence for this task.

Hence, Bayesian optimisation is the most effective method overall, followed by PSO, which offers a good balance of simplicity and quality. The genetic algorithm lags in speed of convergence, and the ant-colony approach is the least justified here.

Accordingly, among the methods considered, Bayesian optimisation is the most appropriate choice for automatic tuning of a server's thermal regime. It locates optimal parameters quickly with a minimum of experiments – crucial for prompt, equipment-friendly adjustment.

The radar chart (figure 9) shows which variables take on higher or lower values for each algorithm.

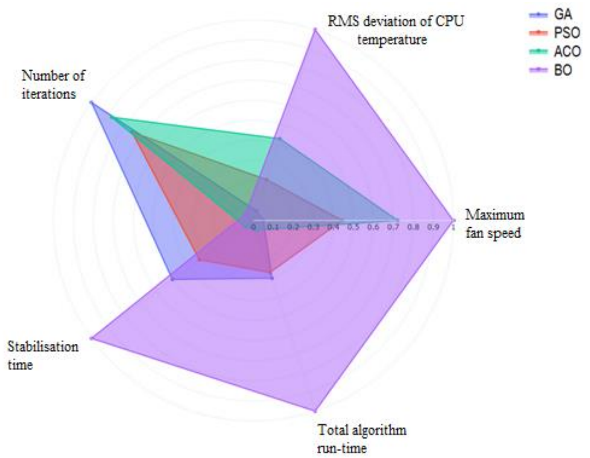

Fig.9 Radar chart comparing the performance of the different algorithms

Figure 10 compares the run-times of all algorithms against the number of iterations.

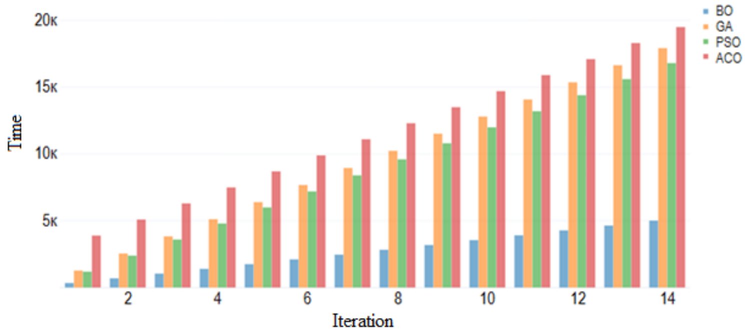

Fig.10 – Comparative run-time of the various algorithms

Implementing the selected Bayesian-optimisation routine and testing it on YADRO VEGMAN servers confirmed that the calculated PID gains maintain a stable thermal regime. Even under pulsed CPU loads, the cooling system with automatic parameter tuning keeps the temperature within safe limits, exhibiting only negligible overshoot and minimal oscillations.

Fan tuning allows processors to remain at optimal temperatures, thereby increasing server reliability. Compared to manual tuning, the proposed approach tunes the cooling system both faster and more accurately.

Conclusions

Of the algorithms considered, the most appropriate choice for the task of automated selection of PID coefficients when setting up the temperature regime of servers is Bayesian optimization. It carries out a quick search for optimal parameters with a minimum of iterations.

we managed to select coefficients that ensure an acceptable temperature regime for the operation of VEGMAN servers, which increases the reliability of the servers.

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