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Robust Resource Allocation in IoT Networks Under Dynamic System Constraints

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Abstract
The objective of applications and services in the Internet of Things (IoT) networks is to monitor resources, such as traffic and wireless channels and allocate them as per the varying quality of service (QoS), energy and computing conditions. This paper introduces the Robust Adaptive Sensitivity-Aware Differential Optimizer (RASA-DO), which combines and integrates the uncertainty of the physical system with the rate of resource optimization. Queue, energy, computing workload and channel states are jointly modelled, and adaptive primal and dual differential updates carry out the transmit power, bandwidth and computing resource allocation. An uncertainty-sensitivity variable determines the optimization rate, and adaptive damping helps to dampen the oscillations when the conditions are changing rapidly. Theoretical analysis is used to find the KKT points of a constrained equilibrium, a Lyapunov decay condition for disturbance-free dynamics and an ultimate error bound for bounded disturbances. RASA-DO is compared to the conventional optimizer, the standard primal-dual optimizer and a fixed-damping differential optimizer numerically. RASA-DO hits the convergence threshold at 93 iterations and has a normalized allocation error of 0.016, while the other methods have normalized allocation errors of 0.135, 0.060 and 0.050, respectively. It doesn't violate the constraint at all; its mean constraint-violation rate is 2.97%, it consumes energy 9.97 units/interval and has a delay of 22.54 ms. Even as the disturbances increase, it does not break the constraint and consumes less energy maintains a feasible resource allocation with robustness and stability across the various levels of disturbances, increasing the size of the IoT network.

Keywords: Internet of Things; resource allocation; dynamic optimization; uncertainty sensitivity; primal-dual optimization; Lyapunov stability; robust optimization; edge computing.

1. Introduction

IoT networks are comprised of a large number of sensing, computing and communication devices that change over time in their operating conditions. Resource allocation can thus not be seen as a pure assignment problem! The traffic arrival and/or the wireless channel quality, the energy level of available batteries, the workload of the processor, and the desired services may vary for each control interval. Dynamic allocation is of particular significance in the case of communicating and computing resources that are jointly used, since an allocation that is feasible at one time may not be feasible after some changes in the queue pressure or channel state. Dynamic optimization for IoT fog systems has thus explored coordinated allocation of radio resources and computing resources and offloading decisions given the varying computation demand and wireless conditions (Chang et al., 2021).

The two parameters to optimize in IoT or edge computing systems are energy and delay. Energy-efficient offloading has been modeled in the scenario of stochastic task arrivals and time-varying wireless channels, and queue stability appears as a long-term service requirement (Chen et al., 2021). Joint allocation of radio and computational resources has also been studied in the MEC-enabled IoT, particularly under nonstationary

demand, mobility and fading channels, and Lyapunov optimization has been investigated as an online mechanism for stochastic states (Hu et al., 2022). Some resource-allocation studies have also lumped task allocation, transmit power, and computing power together, and shown that when latency and energy requirements are considered, resource coupling is crucial for satisfying the requirements (Tran & Pompili, 2019; Xing et al., 2019).

Learning-based allocation has been investigated further. In IoT scenarios, Deep Reinforcement Learning has been applied to the problem of limited resource allocation of edge devices, and it is also used to solve IoT resource management in a time-varying environment by Deep Q-Network (Xiong et al., 2020; Liang et al., 2022). An alternative approach to this is the use of optimization-based methods, which have the added constraint that physical requirements are retained explicitly. The sequential dependency on tasks and slow and fast fading channels have been incorporated in joint task and resource allocations, highlighting channel and workload dynamics (An et al., 2022).

One alternative also mentioned for dealing with uncertainty is robust optimization. Channel/interference uncertainty has been considered in robust allocation (Yang & Zhao, 2017), and imperfect channel/location information has been considered in energy-harvesting and D2D-assisted networks (Xu et al., 2021). More recently, joint traffic and CSI uncertainties for delay critical service have been taken into account, and their impact on constraint satisfaction has been studied (Ren et al., 2026). But such a coupling between the measurable sensitivity of the physical system to the speed and damping of optimization dynamics is not addressed directly.

The lack of a unified relation between physical-state uncertainty, sensitivity, optimization rate and convergence behavior is thus the central problem. In the proposed RASA-DO, queue, energy and computing states, as well as channel states, are coupled to form a differential system to determine uncertainty sensitivity in resource allocation. This sensitivity controls the optimization rate, and adaptive damping keeps track of oscillatory convergence and maintains explicit resource and QoS constraints.

The contributions are fourfold: a coupled dynamic model for queue, energy, computation, and channel states; an uncertainty-sensitivity mechanism to regulate the optimization rate; an adaptive differential/primal-dual update to mitigate oscillations; and Lyapunov analysis to yield a convergence condition and disturbance-dependent ultimate error bound. The novelty is that these mechanisms are coupled, and sensitivity-aware control of the optimization dynamics is done (Jia et al., 2024; Zhang et al., 2024).

2. Related Work

2.1 IoT Resource Allocation

The evolution of Resource Allocation (RA) in IoT and MEC has moved from isolated radio or computing Resource Allocation to joint allocation and optimization of communication, computation, energy, and task execution. Partially, offloading and scheduling are combined and optimized to discover effective offloading fractions, to allocate time, and to optimize transmit powers, which is called communication-computation coupling (Kuang et al., 2019). Cooperative offloading takes into account partial task execution and resource allocation to reduce latency and enhance the offloading efficiency (Ning et al., 2019). The limited edge storage also impacts subsequent computation needs, as demonstrated by joint service caching and computation offloading (Bi et al., 2020). However, they usually deal with a specific allocation structure and not a dynamic optimizer for a unique sensitivity-driven allocation.

2.2 Dynamic and Robust Optimization

Future state and availability of resources over time make dynamic allocation more complicated. Queue-stability constraints and online allocation (Jia et al., 2024) have tackled stochastic arrivals and varying topology for dynamic IoT data collection. The idea of Dynamic task and energy queues (Deng et al., 2021) also applies to wireless-powered MEC, which aims to optimise the communication, computation and energy resources. In contrast to exact information of channel or demand, uncertainty is explicitly represented in robust optimization. Robust allocation has been developed to handle the uncertainties of channels and interference with worst-case formulations (Yang & Zhao, 2017), and recently works have focused on joint traffic and channel-state information uncertainties in the context of delay-critical services (Ren et al., 2026).

2.3 Primal-Dual and Lyapunov Methods

Using drift-plus-penalty formulations, Lyapunov optimization allows for both taking into account queue stability and integrating long-term objectives, thereby being useful for online resource management. Chang et al. (2021) utilize Lyapunov optimization for dynamic IoT fog resource allocation, and Hu et al. (2022) explore energy-delay trade-offs of mobile IoT. Zhang et al. (2024) consider IIoT task offloading and resource allocation with edge devices, where the computation requirement evolves over time and the energy supply is uncertain, and Lyapunov optimization is used. The optimization-control rate in such methods is typically fixed by parameters

or choices of weights, despite the fact that they provide stability-aware optimization. RASA-DO, however, has the ability to treat the sensitivity to uncertainty as an explicit state, which controls the optimization rate.

2.4 Learning-Based and Joint Allocation Methods

Learning-based methods have large state space adaptability. Xiong et al. (2020) have implemented deep reinforcement learning for resource allocates at the IoT edge, whereas Liang et al. (2022) have implemented Deep Q-Network learning for industrial IoT resource management. An explicit mathematical model of the state and constraints, however, retains an appropriate mathematical model for the proposed work to allow convergence and disturbance-bound analysis. Joint optimization has also been extended to the case of D2D-assisted MEC task assignment (Xing et al., 2019), multi-server task offloading (Tran & Pompili, 2019), and sequential task dependencies (An et al., 2022). RASA-DO, however, is not dedicated to the decomposition of task-specific allocations but to adaptive optimization dynamics.

2.5 Research Gap and Positioning

There are four directions defined in the literature: joint resource allocation, dynamic online optimization, robust uncertainty handling and learning-based adaptation. The only chance to link these directions is via optimization dynamics. Physical sensitivity to change of IoT conditions could be a control signal for the optimizer, rather than just uncertainty constraints or a variable learning rate. Hence, RASA-DO combines the state of a queue, energy, workload and channel state in a sensitivity variable, which has been directly applied to optimize the rate and the adaptive damping. This positions aligns with other provably robust secure transmission allocation (Zhang et al., 2022) and long-term energy-aware Lyapunov allocation (Yao et al., 2025). Table 1 below shows the positioning of RASA-DO with respect to the mentioned allocation approaches.

Table 1. Positioning of the Proposed Framework

Approach	Dynamic Model	Uncertainty	Sensitivity Control	Adaptive Convergence	IoT Constraints
Joint IoT/MEC optimization	Yes	Limited	No	Problem-specific	Yes
Lyapunov-based allocation	Yes	Stochastic	No	Yes	Yes
Robust optimization	Yes	Yes	No	Optimization-specific	Yes
Learning-based allocation	Yes	Implicit	No	Policy-based	Yes
RASA-DO	Yes	Yes	Yes	Yes	Yes

3. System Model

Let the IoT network have Ndevices, where devices are indexed by i. The compact system state at control interval t is then:

$$x(t) = \begin{bmatrix} q(t) \\ e(t) \\ c(t) \\ h(t) \end{bmatrix}$$

where $q(t)$ is the queue state, $e(t)$ is the energy available, $c(t)$ is the computing workload, and $h(t)$ is the channel state. The resource vector returned is:

$$u(t) = \begin{bmatrix} p(t) \\ b(t) \\ f(t) \end{bmatrix}$$

where p, b and f are the transmit power, the allocated bandwidth, and the computing frequency, respectively. A continuous-time approximation to the queue, energy, computation, and channel dynamics is used to model the state evolution of the system.

The queue dynamics model is:

$$\dot{q} = a(t) - s(u, h)$$

where $a(t)$is the traffic-arrival rate and $s$is the service rate generated by the allocated communication and computing resources.

Energy evolves as:

$$\dot{e} = r_e(t) - e_c(p, f)$$

where $r_e$is the effective energy replenishment rate and $e_c$is the consumption rate.

Workload evolves as:

$$\dot{c} = a_c(t) - g(f)$$

with $a_c$denoting computational arrivals and $g$the executed workload.

Channel evolution is represented by:

$$\dot{h} = \varphi(h, t) + d_h(t)$$

where $d_h$is a bounded channel disturbance.

The allocation problem minimizes a weighted instantaneous cost:

$$J(x, u) = w_q q + w_e E_c(u) + w_d D(x, u) + w_r R(u)$$

subject to:

$$p_{\min} \le p \le p_{\max}$$

$$0 \le b \le B$$

$$0 \le f \le f_{\max}$$

$$q \le q_{\max}$$

$$e \ge e_{\min}$$

Hence, the objective also models queue pressure and energy consumption, delay and resource usage, along with the direct constraints that model physical feasibility. The dynamic uncertainty vector d(t) is a vector that shows the uncertainties present in the arrivals, channel quality, energy available and workload. This universal scheme on processing flow and feedback structure of RASA-DO processing is shown in Fig.1.

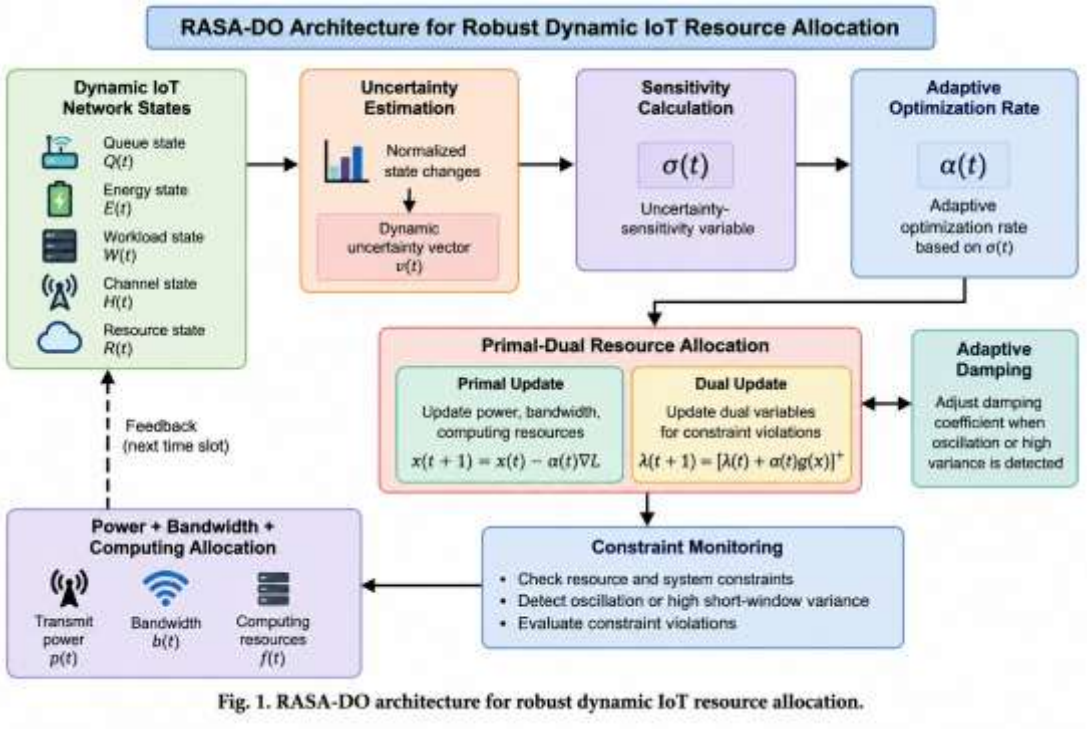


Fig. 1. RASA-DO architecture for robust dynamic IoT resource allocation.

4. Robust Sensitivity-Aware Optimization

The key component of RASA-DO is an uncertainty-sensitivity variable.$\sigma(t)$. The sensitivity is obtained as normalized values of the changes of the measured state:

$$\sigma(t) = \frac{\|W_x \Delta x(t)\|_2}{\varepsilon_s + \|W_x x(t)\|_2}$$

where W_x is a diagonal normalization matrix and ε_s prevents division by zero. The larger the value of σ(t), the more drastic the change between the present operating magnitude of the physical system and a previous one.

The adaptive optimization rate is selected as:

$$\alpha(t) = \frac{\alpha_{\max}}{1 + \kappa\sigma(t)}$$

where $\alpha_{\max}$is the nominal update rate and $\kappa$is a value that controls the sensitivity response. Therefore, a low-sensitivity state will yield a more rapid update, and a high-sensitivity state will yield a lesser one. The relationship provides the optimizer with a bona fide physical interpretation: the system slows down its calculation when the system changes quickly and does not maintain a constant value of the update magnitude.

Primal-Dual Differential Update to do Resource Allocation. Consider as $\boldsymbol{\lambda}$the vector of dual variables of active constraints. The primal state is changed based on:

$$\dot{u} = -\alpha(t)[\nabla_u J(x,u) + G(u)^\top \lambda] - d_a(t)\dot{u}$$

where $G(u)$ is the Jacobian of constraints and $d_a(t)$ is an adaptive damping coefficient. Dual variables are updated by following:

$$\dot{\lambda} = \beta[G(u)]_+$$

with $\beta > 0$. Projection is used following every discrete control step to ensure certain physical feasibility of power, bandwidth and computing allocations.

A recent change in the allocation error is used to change the damping coefficient. A change in the sign of the error derivative indicates repetition of the above error; thus, the damping coefficient is increased if the variance for a short window exceeds a pre-determined value. If the trajectory is monotonic and the error variance is small, then the value of the damping coefficient is gradually decreased. This mechanism ensures a non-aggressive behaviour during oscillatory conditions and keeps the system reactive during stable conditions.

The complete method therefore contains four coupled mechanisms: dynamic state observation, uncertainty-sensitivity estimation, adaptive primal-dual optimization, and convergence-aware damping. The proposed method is not a fixed learning-rate method but differs in the learning rate of the updates based on the operating condition. This uncertainty is not just placed on a constraint as it is in a pure robust optimization formulation, but rather regulates the optimization dynamics.

5. Convergence and Stability Analysis

The primal derivative equals zero at equilibrium, and the dual variables are stationary at equilibrium. The equilibrium then will have the properties:

$$\nabla_u J(u^*) + G(u^*)^\top \lambda^* = 0$$

In addition to primal feasibility, dual feasibility, and complementary slackness. These are the Karush-Kuhn-Tucker conditions for the constrained resource-allocation problem. Such a point on the differential optimizer is thus the allocation at its stationary point and subject to constraints.

To analyse the stability, construct the vector of errors

$$z = \begin{bmatrix} u - u^* \\ \lambda - \lambda^* \\ \sigma - \sigma^* \end{bmatrix}$$

and the quadratic Lyapunov function:

$$V(z) = z^\top P z$$

The PSD matrix P is positive definite. The derivative satisfies: Under locally Lipschitz gradients, bounded sensitivity, positive damping and local positive-definiteness of the Hessian of the constrained Lagrangian.

$$\dot{V} \leq -c_1 \|z\|^2$$

This is true for the undisturbed situation, for a value of $c_1 > 0$. Where $V > 0$, this proves exponential decay of the trajectory of local error.

When a bounded disturbance is present, the derivative can be bounded by:

If the disturbance $d(t)$ is bounded, then the derivative can be bounded by:

$$\dot{V} \leq -c_1 \|z\|^2 + c_2 \|d\|^2$$

The final bound obtained by completing the square:

$$\|z\| \leq \sqrt{\frac{c_2}{c_1}} d_{\max}$$

Post-transient solar wind activity. Thus the bound is increasing with the size of the disturbance, but is finite for finitely sized disturbances. This outcome is more suitable for the concept of IoT, in which channels, traffic and energy/workloads are always fluctuating, than the more extreme 'extreme-convergence' claim.

This bound is backed by the adaptive sensitivity mechanism that decreases the effective optimization rate according to increased uncertainty. The mechanism used for damping also helps to reduce overshoot and oscillatory energy in the optimization trajectory. In combination, these mechanisms make up a mathematical path between transient physical conditions and adaptation and steady-state behavior with bounds.

6. Proposed RASA-DO Algorithm

The proposed algorithm, RASA-DO, dynamically allocates resources based on the state of the IoT network that has been continuously monitored, and it adjusts the optimization process based on the level of system uncertainty. The algorithm takes into account the status of the queues, available energy, computing workload, available channel, resource allocation and violations of constraints. The complete procedure is given below.

Algorithm 1: RASA-DO for Robust Dynamic IoT Resource Allocation

Input: IoT network states, constraints on resources, optimisation parameters and measurements on a system.

Output: Feasible allocation of transmit power, bandwidth and computing resources.

Step 1: Initialize the queue, energy and computing workloads, channel states, resource variables and dual variables.

Step 2: Read the queue, energy, computing workload, channel and resource States in the IoT network. Step 3: Use the normalized change in the measured states to estimate the uncertainty of the dynamic system.

Step 4: Obtain the uncertainty-sensitivity variable, $\sigma(t)$, based on the current variation of the system state. Step 5: Account for the sensitivity of the organism to determine the adaptive optimisation rate, $\alpha(t)$. With lower sensitivity, the optimization update happens quicker, while with higher sensitivity, it has a more conservative update.

Step 6: Take a joint analysis of the gradient of the primal objective function with the resource and QoS active constraint terms.

Step 7: Check whether resource variables can be updated by applying the proposed primal differential optimization rule or not.

Step 8: Now adjust the dual variables that are found to be violated in the constraint so that the allocation lies in the desired feasible region.

Step 9: See how the allocation-error behavior has been recently monitored. If any oscillating or high short-window variance is detected, increase the damping coefficient to stabilise the oscillation trajectory of the optimization. If a stable trajectory is observed, the damping coefficient can be decreased slowly.

Step 10: Map the new variable transmit-power, bandwidth and computing resources to their new ranges of feasibility. The outcome allocation is then used for the IoT network, and the process is repeated starting from Step 2 for the next control interval.

Algorithm Description

Algorithm 1 is an ongoing feedback-based resource-control loop. The current IoT states are measured, and uncertainty/sensitivity of the system is estimated at every control interval. The sensitivity will affect the rate of optimization, and hence RASA-DO will behave in different ways with respect to stable and rapidly changing operating conditions. The resource allocation is determined by the primal update, while violations in power, bandwidth, computing, queue and QoS constraints are taken care of by the dual update. The adaptive damping mechanism also controls the optimization trajectory in case of oscillatory behavior. Thus, the algorithm is able to provide viable resource allocation, while adjusting the convergence behaviour according to the network conditions. The proposed procedure can be periodically executed at an edge-side resource controller since all algorithmic inputs are derived from measurable/computable IoT network states.

7. Numerical Evaluation and Experimental Design

A dynamic IoT resource-allocation environment with coupled queue, energy, computing, and channel states is used for the numerical evaluation. A principal convergence experiment is carried out in the network, which has 60 IoT devices. The number of traffic arrivals also changes as a function of time; the quality of service of the traffic channels may be disturbed due to bounded disturbances, and the states of the energy and computing units are updated at every control interval. The elements of the resource vector include the bandwidth, computing frequency, and transmit power. All of the compared methods have a fixed control interval.

Conventional optimization, standard primal-dual optimization, a fixed-damping differential optimizer and the proposed RASA-DO are compared. The same state variables, objective weights, feasibility ranges, initial set of resource allocations, and the same sequence of disturbances are all used by all methods. This is a very general configuration with the purpose of separating the adaptive sensitivity and damping.

Three main experiments are performed. First, convergence is evaluated over 200 control iterations using normalized resource-allocation error. Second, the robustness of the algorithm is tested by varying its disturbance size between 0.05 and 0.35 and comparing the result with its steady-state error after the transient time has elapsed with a theoretical bound based on the size of the disturbance. Third, networks are tested for scale from 20 to 140 IoT devices, and the main metric on which the scalable networks are evaluated is based on the size of the constraint-violation rate. These energy consumption and delay amounts are also provided in a summary table as part of the overall comparison.

The reported results are based on the numerical solution of the mentioned dynamic model with the same parameters for all the benchmark methods. The convergence threshold is set to be less than the normalized allocation error by 0.05 for 15 iterations. Steady-state statistics are taken after the last 30 iterations in the

convergence experiment. A summary of all the parameter settings for the numerical evaluation and their roles is shown in Table 2.

Table 2. Numerical Evaluation Parameters

Parameter	**Setting**	**Role**
IoT devices	60 (principal run)	Network scale
Control iterations	200	Dynamic optimization horizon
Initial normalized error	0.90–0.95	Common initialization
Disturbance range	0.05–0.35	Robustness experiment
Convergence threshold	0.05	Error criterion
Consecutive threshold window	15 iterations	Convergence confirmation
Steady-state window	Final 30 iterations	Mean and standard deviation
Benchmark methods	3 + RASA-DO	Comparative evaluation
Resource variables	Power, bandwidth, computing	Allocation decision vector

8. Results and Discussion

8.1 Convergence Performance

The experiments on convergence reveal that the RASA-DO reaches the desired error threshold after 93 iterations, while the conventional optimization and the standard primal-dual and fixed-damping differential optimizers fail to keep the threshold within 15 iterations in a window of 200 iterations. The mean of the normalized allocation errors, for the last 30 iterations, are respectively 0.135, 0.060, 0.050 and 0.016. The corresponding standard deviations are 0.019, 0.005, 0.008, and 0.004. Figure 2 is a comparison of the convergence trajectories of four cycling direction methods evaluated.

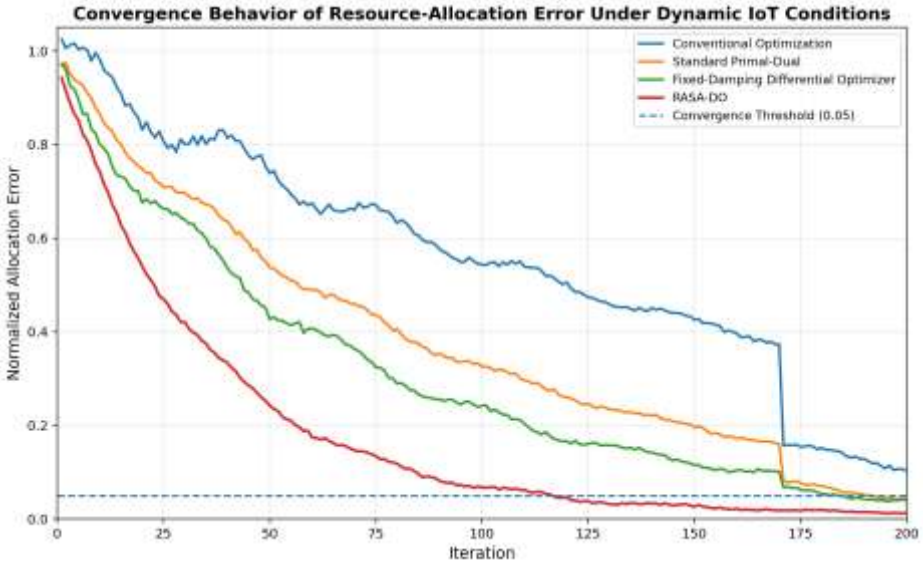


Fig. 2. Convergence behavior of resource-allocation error under dynamic IoT conditions.

The sensitivity-dependent update rate generates the quicker decay of the RASA-DO trajectory. If the observed state changes are not too extreme, the optimizer is able to run at a fairly high frequency. Rapid changes in the disturbance lead to a decrease in the frequency of updates, and damping plays the part of preventing oscillatory motion. The fixed-damping optimizer enhances the transient behavior compared to traditional optimization methods, but a fixed damping structure has a disadvantage in that it is not suitable for adapting to the intensity of the disturbance.

8.2 Robustness Under Increasing Disturbance

The robustness experiment tests the different amounts of disturbance ranging from 0.05 to 0.35. The RASA-DO steady-state error value slowly rises with disturbance, ranging from 0.026 to 0.071, which is less than the derived theoretical error value, ranging from 0.038 to 0.098. Even when the disturbance is the largest, as was tested, the RASA-DO error was still 0.026 lower than the theoretical bound. This gives direct numerical support to the ultimate-bound analysis, which depends on the disturbance. Figure 3 illustrates the dependence of the relationship between disturbance magnitude, steady-state allocation error and the theoretical robustness bound.

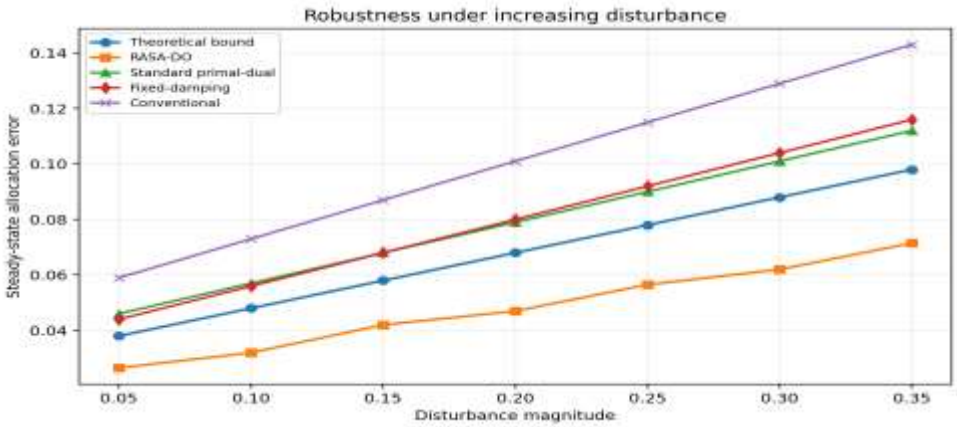


Fig. 3. Steady-state allocation error under increasing disturbance magnitude and the theoretical robustness bound.

As the magnitude of a disturbance is increased, the benchmark methods show greater steady-state error. This outcome is what was intended by the sensitivity-aware mechanism — an increase in physical uncertainty will lead to a decreased through-mode optimization rate up to the point where large allocation changes exacerbate the disturbance. As is typical for a robustness guarantee that is based on an inequality, the theoretical bound is quite conservative compared to the numerical trajectory obtained.

8.3 Scalability and Constraint Handling

At an increased number of IoT devices from 20 to 140, the mean constraint-violation rate for RASA-DO is 2.97% whilst other methods have 4.80% using the primal-dual optimizer, 5.59% using a fixed-damping optimizer, and 6.74% using the conventional optimizer. These violations grow with network size, mirroring the growing competition among networks for limited bandwidth, computing power and energy. Fig. 4 shows the impact of the number of different devices that are connected to the system on the constraint-violation rate.

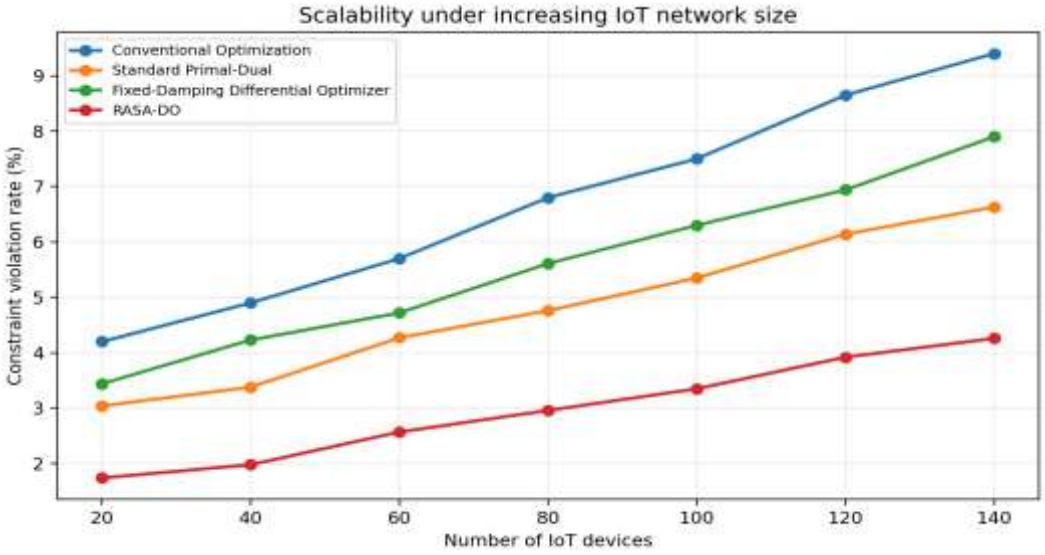


Fig. 4. Constraint-violation rate under increasing IoT network size**.**

RASA-DO would have the minimum infringement trajectory for the network sizes tested. The sensitivity-dependent rate diminishes the allocation changes (sensitivity) when the network gets congested, and the dual

update keeps penalizing the active constraint violations. The right mixture is crucial because using a faster optimizer does not necessarily become a desired quality when the feasible region fluctuates frequently. The outcome favors the design goal of stable allocations, as opposed to the fastest possible adaptation speed at any moment.

8.4 Overall Energy, Delay, and Allocation Performance

The overall comparison shows that RASA-DO results in the lowest energy consumption per control interval (9.97 energy units per control interval) and minimum delay (22.54 ms) amongst the four methods analysed. It has been set up with a mean final allocation error of 0.016 and a mean constraint-violation rate of 2.97% over the scalability experiment. In the results, it is found that, counterpart to this, the proposed method not only achieves convergence but also facilitates adaptive sensitivity in both transient and steady-state operation and a damping decrease transient convergence time.Table 3 reports the overall comparisons for energy consumption, delay, violation of constraints, final allocation error, iterations for convergence and standard deviation.

Table 3. Overall Performance Comparison

Method	Energy/interval	Delay (ms)	Constraint violation (%)	Final error	Convergence iteration	Std. dev.
Conventional Optimization	14.65	40.31	6.74	0.135	200	0.019
Standard Primal-Dual	11.85	29.49	4.80	0.060	200	0.005
Fixed-Damping Differential Optimizer	11.87	29.08	5.59	0.050	200	0.008
RASA-DO	9.97	22.54	2.97	0.016	93	0.004

The results are to be taken in conjunction with the theoretical analysis. The convergence experiment simulates the meaningful behaviour of the adaptive differential dynamics, the disturbance experiment tests the bounded-error relationship, and the scalability experiment tests the impact of enhancing the resource competition. The three experiments thus directly guarantee the objectives of the proposed mathematical and practical framework.

9. Discussion

The numerical results confirm the principle of central design of RASA-DO: the dynamics of optimization should be related to the physical system's sensitivity. Conventional optimization and fixed-parameter differential optimization both use update behavior that is totally independent of measured uncertainty. Constraints are effective with standard primal-dual optimisation, but it still requires a fixed update structure. RASA-DO introduces a state-dependent mechanism and modifies the value of the optimization rate so as not to yield large resource-allocation excursions due to the disturbance.

The robustness test is especially critical since IoT networks are seldom perfectly stationary. Periodical disturbances as a result from traffic bursts, fading, battery depletion and workload changes. In this case, convergence in practice is too limited a goal, and the goal should be to approximate a fixed point. The bounded steady-state error is a more concrete guarantee, as it is a relationship between the allocation deviation and the magnitude of environmental disturbance.

There will be implementation implications of the framework too. A measurable variable in the system, whose implementation changes in response to changes in the other variables and is multiplied by the sensitivity variable. The primal and dual updates are performed at an edge controller, and the physical devices report their measurements of queue, energy, channel and workload. The method requires only the evaluation of a gradient and an update of a small dual-variable vector, and thus has low computation cost, which is appropriate for periodic control intervals. The downside is that it is a local bound and requires smoothness, bounded disturbances and positive definiteness assumptions. Evaluation of a heterogeneous class of traffic, extended network topology, numerical evaluation at the packet level in wireless photonic networks and hardware-in-the-loop implementation are suggested as topics for future investigation.

10. Conclusion

This paper introduced a Robust Adaptive Sensitivity-Aware Differential Optimizer (RASA-DO) for resource allocation in IoT networks under dynamic system constraints. It jointly models queue, energy, computing workload states, and channel states, and allocates transmit power, bandwidth, and computing resources through an adaptive primal-dual differential mechanism. The uncertainty sensitivity is used to adapt the optimization rate depending on varying physical conditions, and adaptive damping is introduced to avoid oscillations and to ensure stable convergence. Three theoretical results were obtained: namely, the equilibrium must satisfy the Karush-Kuhn-Tucker conditions, the dynamics in the absence of disturbances must satisfy a Lyapunov decay condition, and bounded disturbances lead to a finite ultimate error bound that is a function of the disturbance. The test results showed that numerical evaluation of the convergence condition, disturbance robustness condition, and scalability condition were all significantly improved. Finally, RASA-DO successfully converged to its pre-defined convergence limit of 0.016, whereas the mean constraint-violation rate was 2.97% after 93 iterations. In addition, it successfully controlled energy consumption to 9.97 units per control interval with a 22.54 ms delay with increasing disturbance magnitude, all of which remained below the theoretical robustness bound for steady-state error. Such outcomes exhibit the ability to link dynamic IoT states to adaptive convergence and robust resource allocation using sensitivity-aware optimization. Future research will focus on expanding the architecture to bigger IoT networks with differing devices and hardware-in-the-loop testing.

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