# Enhancing Resilience in IoT Networks using Organic Computing: Challenges and Requirements

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**Abstract:** In this paper we present and analyse the requirements and challenges of the Task Allocation Problem for Internet-of-Things (IoT) Networks, especially Wireless Sensor Networks (WSNs). As IoT is comprised of a variety of heterogeneous devices and network configuration may change regularly due to low-power nodes failing or communication disruptions, a static allocation of tasks to individual nodes cannot be assumed. Therefore, task allocation has to be carried out and managed for every dynamic change in the network along the lifetime of the network. In dynamic task allocation, a NP-hard problem, the calculation of a new optimal allocation could quickly become a bottleneck for network performance, giving rise to the need of organic computing solutions to provide self-organised task allocation solutions for such networks.

**Keywords:** IoT; Organic Computing; Dynamic Task Allocation

## 1 Introduction

The Internet-of-Things (IoT) and especially Wireless Sensor Networks (WSNs) are comprised of multiple potentially low-power nodes distributed throughout the environment to monitor, process and manipulate. Nowadays this technology is already used in many application fields like collaborative monitoring [Yu17], traffic control [Ka14], agricultural irrigation [Ou14], intelligent transportation management [Ph10] and environmental monitoring [ZLH13]. The dynamic nature of these applications requires flexible, but reliable distribution of tasks to nodes within the network. This requires reliable reallocation on failures and dynamic optimization of performance on environmental changes. The methodologies in the context of Organic Computing (OC) [MSSU11] offer means to enable controlled self-organisation for IoT applications. OC provides the capability to deal with a large number of entities such as sensors that can work in a self-organised way but at the same time can be controlled and adapted to the environmental changes. One major aspect in OC is the dynamic optimization which involves observation and monitoring the current state of the system and adaptation to possible changes.

This paper aims to provide theoretical foundations for the integration of OC with IoT as the system under observation and control. In contrast to classical OC applications, WSN and

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mobile IoT systems are limited in energy [PAG09]. This induces a new major challenge in the maximisation of the lifetime of the overall system. Therefore, incorporating energy-awareness to the OC components is crucial, especially in use-cases where recharging or replacing the individual nodes or their batteries is infeasible. Consequently, energy efficiency is the key factor in nearly all applications of WSN technology if these want to be adopted by real world users. Typically, energy is drained by four components of each node, the processor, sensors, actuators and the communication system. Among these, the communication is generally the largest energy consumer [Ra02]. Multiple solutions may provide partial remedies for the energy consumption of the communication. The communication can be made more efficient by minimising waiting times and limiting the active time of the receiver. Approaches to optimizing the communication itself have already been intensively studied and may depend on specific hardware requirements. However, a more global optimisation approach could provide additional benefits. Thus, another solution is the optimisation of the allocation of tasks to nodes of IoT Network, especially in multi-hop networks. This allows to minimise communication in the whole network by putting processing in line between data sources and data sinks. Additionally, it allows to balance the energy consumption of the nodes to prevent early battery drainage of single nodes, which may result in a partition of the IoT network into multiple disconnected sub-networks. Unfortunately, this problem is NP-Hard and needs advanced algorithms to be efficiently performed within the network. Classical task allocation algorithms may provide good solutions, but at costs, which already drain the nodes before the task even started.

In this paper we provide an in-depth analysis of the task allocation problem in IoT networks. Our goal is to analyse existing state-of-art solution regarding the challenges of IoT as well as OC and establish a formal model for evaluation and analysis of task allocation methods. Additionally, we review and classify the various methods that have been used to tackle this problem in the literature. The paper is structured as follows: In Section 2, we give a complete analysis of the challenges involved in the task allocation problem. Afterwards, Section 3 provides an overview of the state-of-the art algorithms. We formally describe the model for task allocation problems within IoT networks in Section 4 and conclude the paper in Section 5.

## 2 Challenges

The task assignment problem as an instance of the generalised assignment problem, which is known to be NP-hard [Yu14]. In its most basic form, we consider a network of homogeneous nodes to which a set of independent tasks are assigned. Given $N_N$ nodes and a set of $N_T$ tasks, the total number of possible assignments is $N_T^{N_N}$. Without exploiting additional knowledge on the system, a direct calculation of the optimum allocation is prohibitively expensive for all but even the smallest networks. Additionally, this simplistic model is not applicable for real-world networks. Therefore, the following section analyses additional challenges for IoT networks:

**Task Requirements** The basic problem stated above does not consider any requirements imposed by the tasks themselves. However, in reality multiple requirements may be imposed by certain tasks. The first issue is that not all tasks are independent from each other: A sensing task may have to be performed and the measurement transmitted before that information can be processed somewhere else in the network. These dependencies need to be incorporated into an optimal task allocation, ensuring sufficient and timely information flow to nodes which have to carry out tasks depending on this information. In addition, tasks can have specific constraints, such as a deadline by which a set of tasks has to be finished, which will have to be ensured during task allocation. Tasks will have to be scheduled in a way that the deadlines of all tasks are kept. Critical task sets would have to be allocated to the most reliable nodes in the network, imposing further constraints on task allocation. Additionally, tasks may have a specific sensor or actuator requirement at a specific location, requiring availability of a node capable of satisfying such task constraints.

**Heterogeneity of Nodes** Typical networks consist of nodes with varying processing powers, battery reserves, communication capabilities. Furthermore, each node may have only specialised sensors, such as temperature or humidity sensors. As such, no one-fits-all solution can be implemented and the task allocation algorithm must incorporate the knowledge about differing node capabilities. Furthermore, node capabilities may deteriorate over time as energy levels begin to decrease or environmental conditions change. In theory, bandwidth and topology of the network can be easily determined, but the actual values in practice may greatly differ from this and even differ at different times during network operation. As such, the task allocation algorithms need to incorporate the current state, capabilities of each node, and their link quality to their neighbours, in order to provide optimal solutions.

**Dynamic Network Conditions** Dynamics in networks typically result from failures or mobility of nodes. **Failures** can lead to node or link loss changing the network structure. With the limited power capacity of nodes, it can be assumed that nodes fail during sufficiently long operation times. Additionally, new nodes could be added to extend the capacity of the network during run-time, giving new options for more efficient task allocations. Furthermore, nodes may not be positioned at the same coordinates for the entire duration and may move either due to environmental or other mobility factors. In addition, there may be temporary node outages or disruptions in communication inducing transitional failures. Overall, any single node failure can have extensive repercussions for network structure due to the multi-hop communication model. A Node failure may not only impact the tasks allocated to the failing node, but also other tasks with communication paths incorporating the failed node. As a result, some communication paths may have to be rerouted whenever a node fails, resulting in increasing and shifting task loads to other nodes in the network. **Mobility** of nodes is another aspect causing change in the network structure and possibly invalidating the task allocation. The mobility of nodes is typically intrinsic either because the IoT devices are mobile or due to external forces such as environmental influences. Moving nodes may influence the network communication by disconnecting some links due to increased range and facilitating new links with nodes close to their new positions. Additionally, spacial constraints of tasks involving sensing or acting may be violated because of the movement. Given these dynamic conditions, even an optimal task allocation may only stay optimal for a very short duration of the lifetime of the network and re-allocation is required to be carried out multiple times creating time-varying task allocations. Consequently, efficient and reliable task allocation algorithms that go beyond classical approaches are needed. Network dynamics due to node failures is a well-studied problem, but only few works consider the challenge imposed by node mobility. Jin et al. [Ji13] placed particular focus on network dynamics including node mobility, ensuring an up-to-date solution could always be used when changes of the network structure occur.

**Load Balancing** While achieving high network lifetime for a set of tasks is essential, an aspect that should not be ignored is the balancing of task load among all nodes in the network. As task requirements may change over time or new sets of tasks may be introduced, it is very beneficial to keep a variety of nodes available. In this way, the load can be distributed which can ensure a balanced energy level throughout the network. Load balancing on processing and energy consumption are among the well-studied goals for task allocation and the focus of several works in the literature e.g., [KOT18, ETX12, Gu15].

**Quality of Service (QoS)** Given the above challenges and especially the node failures, it cannot be assumed that communication always is perfect. With wavering link quality between nodes, transmissions might fail or be incomplete and data might have to be resend, increasing the communication costs by factors of two or more as messages might have to be retransmitted multiple times. Therefore, the link quality between pairs of nodes cannot be ignored, as it can have a significant impact on the network lifetime. An additional factor is the quality of the provided sensing, processing and actuating tasks. By assigning the task to multiple nodes, service quality can be improved at the cost of increased energy requirements. This can be measured by the percentage of lost packages, accuracy of sensed information, speed of processing and the ratio between successful and failed actuating tasks. Zhang et al. [Zh19] present an approach especially focused on ensuring the reliability of the task allocation.

**Task Allocation Efficiency** Any allocation of tasks will drain the resources of the network as tasks are moved from one node to another. This requires communication and processing for all involved nodes and has to be incorporated into the network model. As such, an efficient mechanism to redistribute tasks needs to be developed. Otherwise, any performance gained through optimization may be unmade by the cost of applying the new allocation to the network. OC provides means to determine these allocations and decide on the reallocation of tasks. Efficient algorithms nee to minimise the overall reallocation cost by either reallocating seldom or by only reallocating parts of the tasks.

**Network Observation Quality** One of the major strengths of OC is to monitor the system and control whenever necessary. Therefore, network observation plays an important role which enables us to keep track of all the above aspects for the task allocation. Usually, task allocation algorithms depend on having as much and as accurate information as possible to make intelligent decisions about the best options within the network. However, collecting

Tab. 1: Overview of modelling completeness of state-of-the-art approaches

| Reference | Type | Dynamic | Balance | Hetero-geneity | QoS | Obser-vation | Task model | MOO |
|---|---|---|---|---|---|---|---|---|
| [Ji13] | GA | ++ | | + | | ++ | ++ | |
| [HX11] | GA | + | | | + | | + | |
| [KOT18] | GA | + | ++ | + | | | + | + |
| [Gu15] | PSO | + | ++ | | ++ | | + | |
| [Ya14] | PSO | + | ++ | + | | | + | |
| [Yi17] | Consensus | + | + | ++ | | ++ | + | |
| [ETX12] | Auction | + | ++ | | | + | + | |
| [CPA14] | Consensus | + | ++ | ++ | + | + | + | |
| [XZ20] | ACO | + | | + | + | | + | |
| [SLT18] | PSO | + | + | | | + | + | ++ |
| [Zh19] | PSO | + | | | ++ | | + | |

information about each node with high frequency leads to highly increased network load, as every node would need to relay its current status to a dedicated observer node or broadcast it in the network for distributed consensus. This keeps the network information completely up-to-date and reliable, but drains all nodes of energy. This runs contrary to the goal of increasing network lifetime by performing optimisation of the task allocation. With that in mind, perfect information cannot be assumed and an appropriate algorithm needs to incorporate uncertainty of network observations in the decisions making of the OC mechanisms.

**Multi-Objective Optimisation (MOO)** When combining the previous challenges of the dynamic network structure, load balancing, observation quality and allocation cost, it quickly becomes clear that trade-offs are necessary between some of the goals of the optimisation. As such, the task allocation problem needs to be formulated as a Dynamic Multi-objective Optimisation Problem (DMOP): Network lifetime, energy level or consumption balancing, reliability and quality of information may be maximised while minimising the cost to find an optimal allocation and execute it on the network.

## 3 Classification of the state-of-the-art approaches

Considering the above challenges, we provide an overview and a classification of the state-of-the-art approaches from the literature. Table 1 provides a general overview of the recent works in the literature and gives a summary of the incorporated aspects, which map directly to the challenges described in Section 2. A complete handling of a challenge in

Tab. 2: Overview of metrics coverage in state-of-the-art approaches

| **Metric** | **Evaluated in** |
| --- | --- |
| Latency $L$ | [Ji13, Gu15, Ya14, Yi17, ETX12, SLT18] |
| Load Balance $C$ | [KOT18, Ya14, Yi17, ETX12, SLT18] |
| Energy Consumption $E$ | [HX11, KOT18, Gu15, Ya14, Yi17, ETX12, SLT18, Zh19] |
| Reliability $R$ | [Gu15, Zh19] |
| QoI $I$ | [HX11, CPA14, SLT18] |
| Network Lifetime $NL$ | [Ji13, KOT18] |

the model used by the respective authors is denoted by (++) while a partial incorporation or evaluation is denoted by (+). A missing entry means that the particular aspect was disregarded. We additionally specify the generic type of optimisation algorithm being used. As visible, Genetic Algorithms (GA), Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) are the most frequently used meta-heuristics. Additionally, the table shows that Consensus-based methods can help to deal with the observation challenge, while Auction-based methods help to increase the load balance in the network. Nevertheless, it becomes clear that most of the existing approaches only study certain aspects of the task allocation problem in detail while neglecting others. To the best of our knowledge, no work has as of yet been provided which tackles the problem in its complete form.

Several works provide solutions to parts of the DMOP [KOT18, SLT18]. However, as of yet, no work has been put forth that provides a complete solution to all of the defined objective functions (refer to Section 4). Most of the other presented works combine a selected number of objectives into a single objective function using a weighted sum with arbitrarily chosen weights. Table 2 shows the coverage of the various objective functions among the works evaluated in Table 1.

## 4 Formal Problem Description

In this section, we establish a formal model for the DMOP as described in Section 2. In particular, we develop a generic model for task and network structure of a wide range Iot or WSN networks while incorporating the challenges and providing mathematical definitions for the optimisation metrics.

The goal of Task Allocation for IoT networks is to distribute a set of tasks $T_i \in V_{Task}$ to a set of nodes $N \in V_{Nodes}$. To represent the dependencies between the tasks a directed acyclic graph (DAG) $G_{Task} = (G_{Task}, E_{Task})$ is used, as it models relevant problem aspects with little loss of generality. In this model, each vertex of the graph is a task $T_i$ and each edge in the DAG $e_{ij} \in E_{Task}$ represents a directional dependency between the two tasks $T_i$ and $T_j$. Additionally, weight values $w_{ij}$ are assigned to each edge, which represents the data communication cost between the two tasks if these tasks are executed on different nodes. Another weight value $q_i$ is attached to each vertex, which represents the processing cost of the task $T_i$. Finally, a task may be assigned additional spatial constraints $S_i$ to specify where in the network it may be executed. In this model, we consider three distinct task types:

**Sensing Tasks** create information to be relayed to other nodes. These do not possess predecessors in the DAG. Due to the raw sensor information, these tasks typically have either high communication or high processing costs.
**Processing Tasks** possess both predecessors and descendants and have typically high processing costs and no spatial constraints.
**Relaying Tasks** are internal tasks automatically created to forward information and have typically high communication costs and no spatial constraints. These tasks can either be generated by the task allocation or created implicitly by a routing protocol.
**Actuating Tasks** only possess predecessors typically incurring low processing costs.

An example for such a network with two sensing tasks, one processing task accumulating the information from both sensing tasks and one actuating task is shown in Figure 1.

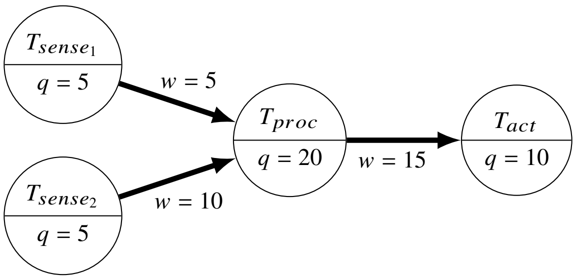


Fig. 1: Basic task graph example

The IoT network is modelled as an undirected graph $G_{Net} = (V_{Nodes}(t), E_{Com}(t))$. Each node $N_i$ is associated with a battery and its specific amount of energy $E_i(t)$ at time $t$ as well as its position $\vec{x}(t)$. Two nodes can communicate if there is an edge $e_{ij} \in E_{Com}(t)$. The set of edges and vertices is time-dependent due to the dynamic nature of the network as nodes and links between nodes may transiently or permanently fail. Each edge is associated an energy consumption $E_{ij}(t)$ representing the amount of energy necessary to forward one unit of information and a latency value $L_{ij}(t)$ modelling the current latency when transmitting data along this edge. Additionally, a function for each node is assumed, which transforms processing cost to latency $L_i(c_j)$.

The problem of task allocation is to find an allocation of tasks to nodes. Formally, this allocation is an injective function $A : V_{Task} \to V_{Nodes}$, which assigns each vertex in the task graph $G_{Task}$ to a non-empty subset of vertices $N_{T_i}$ of the network $N_{T_i} \subset G_{Net}, N_{T_i} \neq \emptyset$. An allocation is valid iff for each Task $T_i$ in the Task-Set $V_{Task}$, there is at least one node $N_j \in V_{Nodes}$ allocated, which fits the tasks' sensor and actuator requirements. Additionally, the node $N_j$ needs to be connected through communication edges $e_{jl} \in E_{com}$ with all nodes $N_l = A_t(T_k)$ executing directly connected tasks $e_{ik} \in V_{Tasks}$. Since the Network may change its structure over time and communication conditions are unlikely to remain the same, the goal is to find a series of valid allocations $A = A_0, A_1, \ldots, A_n$ with associated start times $t_i^{start}$ and end times $t_i^{end}$. For each time $t$ the respective allocation is defined as $A_t = A_i, t_i^{start} \leq t \leq t_i^{end}$. Overall the allocation series shall maximise Network Lifetime $NL(A)$, Network Energy Balance $C(A)$, Reliability $R(A)$ and Quality of Information $I(A)$ while minimising Latency $L(A)$ and Energy Consumption $E(A)$.

The Network Lifetime $NL(A)$ is defined as the maximum time where a valid Allocation $A_i$ exists:

$$NL(A) = \max(t_i^{end}), \text{where } A_i \text{ is valid} \tag{1}$$

The latency $L_{ij}$ for each connected pair of nodes $i, j$ is given by the edge weights $L_{ij}$ connecting them. The latency between dependent tasks $T_k, T_l$ can thus be defined as the sum of all edge weights along the path $P_{kl}(A)$ plus the latency $L_k(q_i)$ generated through processing of Task $T_k$ on Node $N_i = A_t(T_k)$ on their assigned nodes. The latency $L(A_t)$ of the allocation $A_t$ is defined as the maximum latency of all connected sub-tasks, see Equation 2.

$$L(A_t) = \max_{T_k, T_l \in V_{Tasks}} \sum_{e_{ij} \in P_{kl}(A_t)} L_{ij} + L_i(q_k) \tag{2}$$

The load balancing in the network directly relates to the distribution of energy consumption between the nodes. This energy consumption distribution can be calculated as shown in Equation 3, where $E_j(A_t)$ is the total energy consumption of Node $N_j$ based on the assigned tasks and $\overline{E}(A_t)$ is the estimated average energy consumption for all the nodes at time $t$.

$$C(A_t) = \sqrt{\frac{1}{N_N} \sum_{N_i \in V_{Nodes}} \left[E_i(A_t) - \overline{E}(A_t)\right]^2} \tag{3}$$

The energy consumption of the task set $E(A_t)$ at time $t$ is defined as the sum of the energy consumption of all nodes in the network:

$$E(A_t) = \sum_{N_i \in V_{Nodes}} E_i(A_t) \tag{4}$$

For the reliability of the communication links, we refer to Zhang et al. and their work on a reliable Task Allocation Method [Zh19]. The proposed reliability metric $R(A_t)$ incorporates both the reliability of nodes and the links between them. The reliability for a task allocation is then calculated by combining the reliability of all assigned nodes and all transmissions along the network graph.

Quality of Information (QoI) can be measured through the amount and quality of sensors providing information for a sensing task. A simple approach is to define QoI $I(A)$ as the sum of the quality of the sensors $I_j$ of the nodes $N_j$ for each sensing task $T_i$, see Equation 5.

$$I(A_t) = \sum_{T_i} \sum_{N_j \in A_t(T_i)} I_j \tag{5}$$

The different objective functions need to be combined with the network and task specification to the full Dynamic Multi-Objective Optimisation Problem (DMOP), see Equation 6.

$$\begin{aligned} &min\,(L(A), C(A), E(A), -NL(A), -R(A), -I(A)) \\ &s.t.\ \forall t \in [t_0, NL(A)], A_t \text{ is valid} \end{aligned} \tag{6}$$

With all the above elements incorporated, the resulting DMOP combines all aspects of the state-of-the-art literature into a unified model capable of representing a wide range of Task Allocation Optimisation Problems and the associated challenges.

## 5 Conclusion

This paper provides an overview of the challenges in IoT systems incorporating OC mechanisms to enable resilience and performance through online optimisation. We have addressed the OC characteristics with IoT features regarding energy consumption, which imposes the major limitation for both approaches. The task allocation problem for IoT networks imposes a variety of challenges to overcome. In its entirety, it represents a Dynamic Multi-Objective Optimisation Problem (DMOP), which poses a major challenge itself. We propose a model to formally evaluate and analyse algorithmic solutions for this DMOP, which is general enough to cover most conceivable networks and task structures. For future work, it is necessary to develop and evaluate algorithms which tackle the full DMOP using the proposed model and compare their results and performance with existing solutions in centralised and decentralised approaches. Due to the complexity of the problem, a framework of algorithmic building blocks needs to be developed to allow the adaptation of the algorithms to the practical problem to minimise the overhead in terms of communication, processing and reallocation.

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