Organic Wireless Sensor Networks: A Resilient Paradigm for Ubiquitous Sensing

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ABSTRACT

We advocate for a novel paradigm in Wireless Sensor Networks (WSNs). As a technology, it has evolved to a scalable networking paradigm with minimalistic operational mandates. However, inherited design principles of static functionality, that are predetermined at design stage, hinder WSN evolvement. More importantly, while we design WSNs to endure harsh environments and scale in both urban and remote settings, we neglect two major factors. The over-deployment of WSNs renders many sensing nodes redundant in functionality, and inflates the cost of running applications; not to mention the resulting medium contention. In this paper we present a novel approach to expanding the operational scale of WSNs by adapting to the environment in which it is deployed. That is, capitalizing on an organic approach in thriving on available resources in the region of interest to reduce deployment cost, and solicit incentivized interaction among communicating resources to deliver dynamic sensing. Not only does this span a new dimension of reliability, over garnered resources, but presents a novel approach to assigning sensing tasks to available resources in correlation to their abundance and serviceability. We present our performance evaluation of reduction in operational costs, and the uptake of sensing tasks by neighboring resources via extensive simulations. We aim to benchmark WSN operational versatility and present a rigorous basis for evaluating the ability of WSNs to resiliently scale to new applications as well as handle intermittent and permanent failures.

Categories and Subject Descriptors

C.2.1 [Computer-Communication Networks]: Network Architecture and Design – *Wireless Communication*, C.2.3 [Computer-Communication Networks]: Network Operations – *Network Management*

General Terms

Algorithms, Management, Design, Reliability.

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Keywords

Novel WSN paradigm; Resilience Benchmark; Resource-Reuse; Elastic Incentives; Maximal matching; Dynamic WSN operation.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have evolved over a wide spectrum of applications. Over the years we have witnessed a considerable drive to optimize the energy footprint of sensing applications, their resilience to failures and scalability; both in density (per unit area) and spread (over deployment regions).

In recent years, the mounting density of deployments has generated overwhelming underutilization of resources across multiple WSNs. Practitioners seldom consider the wirelessly accessible resources in the vicinity of a deployment region, only – at best – incorporate their RF interference and impact on link quality [1][2]. This includes the proliferation of smart devices that harness significant communication and sensing resources, in addition to static (mostly municipally owned) sensing architectures. As such, the design stage is mostly tailored to the application requirements under operational and budgetary constraints. The problem is further complicated by assuming that once nodes are deployed, they will continue to do what they were initially designed to do (static application space) and will communicate only with in-network nodes (black-boxes to all other networks).

In this work we advocate that future WSNs should not develop on a premise of black-box deployments. That is, given a set of resources in a given node, it should be able to cope with changes in application requirements, and neighboring networks with common goals should be able to solicit the utility of local resources to improve performance; for a fee. We argue that WSNs should *organically* span new application requirements, and interact with neighboring networks to evolve and sustain resilience. As such, the sustained operation would be a factor of the environment in which a WSN thrives, and how well it could interact – and potentially barter – with neighboring resources.

It is important to highlight that this paradigm stems from a debilitating underutilization of visible resources, hindering the potential for dynamic operation and post-deployment changes in WSN duties; especially resource-rich nodes that visit our region of interest. The importance of incorporating transient resources stems from their pervasiveness projected uptake in the near future.

First, we note that a resource is defined as a component with predetermined functional capabilities, and the means (e.g., wireless transceivers) to interact with the network. A rigorous

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definition is discussed by [3] in the static case, and [4] in the dynamic case where transient resources pass by the WSN region of interest.

This paradigm targets a dynamic facilitation of running concurrent applications over a group of connected WSNs. This is not a mere aggregation of the pre-deployment applications to which they were engineered, but more importantly to the new applications that emerge in the field of deployment, to which current resources could adapt and serve. In fact, our long term target is to establish a benchmark for WSN resilience in terms of sustaining functional requirements beyond the death of its constituting sensor nodes. Practically, we extend the definition of functional lifetime coined by Dietrich and Dressler in [5] to extend to network life that is sustained by probed resources in the field of deployment. Thus, both functional changes and maintaining operation to serve a given application set, becomes a sheer factor of re-assignment of tasks to available resources.

We thus summarize our core contributions in (1) presenting a novel Organic-WSN paradigm that adapts to resources in the deployment region to boost resilience, functional capacity and lifetime, (2) introduce a new benchmark for extending functional lifetime as a function of communicating resources that are incentivized to contribute with their resources, and (3) present a dynamic heuristic for optimizing network performance over available resources, via a maximal-matching formulation.

The remainder of this paper is organized as follows. In Section 2 we detail the pertinent background to this work, highlighting the foundational contributions in [3][4][6], in addition to current cloud-sensing paradigms that target versatile WSN operation, and related work on post-deployment modifications in WSNs. Section 3 elaborates on the O-WSN model in general, highlighting the role of transient resources. The core of this work is presented in Section 4 as we detail the incentive schemes that will entice contribution from neighboring resources for O-WSN to thrive, and the elastic pricing model that enables dynamic assignment of resources to applications as they emerge. We present our performance evaluation of O-WSN in Section 5, and conclude in Section 6 with remarks on future work.

2. BACKGROUND AND MOTIVATION

The argument for O-WSN builds upon the resource reuse (RR) WSN paradigm presented in [3] [4]. The vision of this work is that future large-scale integrations would facilitate an abundance of resources that are ubiquitously available in the vicinity of WSNs. As such, maintaining and improving operation would be a function of integration and cross-network utilization, rather than that of re-deployment and over-deployment.

2.1 The case for Resource Reuse

Intrinsically, WSNs serve a simple goal; namely to collect data from a sensed field and report back to the sink(s). In the early days of WSN applications, the cost of components and limited scope of applications deemed WSN design a mere branch of embedded-systems engineering. Simply put, designers would engineer the optimal component configuration stringent environment and cost constraints. The resulting network was designed to do that in a black-box model.

This coupling between design and application is not a requirement for WSNs, yet a mere inheritance. Today, WSNs are deployed in environments where not only could the applications change, but the operational mandates of the network could drastically impact operation post deployment. Accordingly, Oteafy and Hassanein presented a Resource-Reuse WSN paradigm in which the design phase constitutes integrating components that would serve the current application, and future manifestations of new requirements. The idea was built on an intrinsic decoupling of WSN design from application requirements, and focusing on the accessibility of resources that are within the WSN.

To enable such a paradigm, the need for a rigorous and unified set of attributes to define what a resource is (Transceiver, memory, MCU, sensor, etc) was presented in [3]. On the other hand, an atomic functional decomposition of application requirements in terms of attributes that wold match the descriptors of resources, was also introduced. Thus, WSN design and operation was reduced to an assignment problem, to which a linear optimization approach was used an evaluated in [3] and [6].

2.2 Crowd sensing

The abundance of smart devices has enabled a new model for sensing networks, dubbed crowd/public sensing. The notion simply builds upon the aggregation of collected data from a diverse group of users who are willing to provide sensing tasks, either via active reporting or passive participation. Many services developed around this model, such as Cosm[™] (previously Pachube). However, it is important to note that public sensing is not a WSN paradigm. It lends itself to some literature on data aggregation and fidelity checking, yet the core concepts of how the two paradigms operate are different.

For one, reporting is a function of when the users (whether passively or actively) report their findings. This could be based on dedicated hardware, generic smartphones with dedicated applications, or simply text (SMS) reporting. Most of public sensing research takes place under the participatory sensing paradigm. This is largely due to ensuring an acceptable level of data quality and reducing the overhead of filtering and verification.

2.3 WSNs Post-deployment

Traditionally, limited deployments in terms of size and scale, allowed practitioners to re-visit the field of deployment to perform maintenance. Moreover, most initial deployments where deterministic in their region of operation, and witnessed limited/no mobility. Thus, intervening in the field of deployment incurred few hardships (at least on field).

In a technology that is advancing on the premise of large scale deployments and self-healing operation, this is evidently short term practice. Even more, potential (and currently practiced) deployment in hazardous/inaccessible terrains deems this approach impossible. Researchers have invested significant efforts in realizing autonomous operation and maintenance of WSNs. The scale and diversity of WSN operation should not have an effect on its post-deployment maintenance; however this is the trend in current literature. This is a direct result of the applicationspecific design that governs SN operation.

3. O-WSN MODEL

In O-WSM, the operation of a WSN is defined over a set of distinct resources with predefined operational attributes. The typical view of sensing nodes inherently encompassed the resources it holds (such as transceivers, sensors, etc). However, in O-WSN we formally define a resource as

Definition 1: A resource is as an active entity in the network with pre-known functional capability, and the means to communicate its capability. Each resource has the capacity to cater for $\mathbf{r}_{\mathbf{k}}$ requests, where $\mathbf{r}_{\mathbf{k}} \geq 1$. Thus, it has $\mathbf{r}_{\mathbf{k}}$ instances.

3.1 Resources and Functional Requirements

We adopt a model where applications are defined in terms of a dissection of functional requirements, which are coupled with the underlying resources of nodes. A significant notion presented here is the cost for using a resource. Since we now expand to include resources that do not necessarily belong to one proprietary, the utilization of resources across different networks is intrinsically a question of cost vs. utility. That is, how much would network owner **A** charge network **B** to use a given set of **A**'s resources. We argue that cross-network resource utilization is in fact a mutually profitable architecture. That is, a resource that is owned by **A** could generate revenue while idle.

The scope of improvement we aim for stems from a unique problem. Our prime concern is not sheer scarcity of nodes or operational efficiency; but the utilization of resources currently in the field of deployment. In O-WSN, we elaborate on the utilization of in-field resources, especially transient ones, highlighting their utility, predictability and usage tradeoff that dictate the efficiency of relying on them for network operations. These attributes are detailed in Section 3.2. The core competency of a WSN in this paradigm is handling the sheer number of resources, both static and transient, that constitute its resource pool (ReP). Thus we first dissect the group of resources that would contribute to the resource pool as either static or dynamic resources, as depicted in Figure 1.

Thus, the network is an aggregation of resources polled form static nodes n^{S} and transient nodes n^{T} . The ReP is an aggregation of these resources. However, n^{T} have deterministic sojourn times that are coupled with spatial limitations. Hence, we introduce the notion of dissecting the WSN deployment space into regions, and assume the presence of an entity dubbed the **Arbitrator**, in each one of those regions. Thus, the locality and relationship with n^{T} would be dictated by their relative position to an Arbitrator. These spatial correlations are elaborated upon in Subsection 3.2.2.

3.2 Capitalizing on abundant resources

The capital gain of O-WSN is utilizing abundant resources in the field of deployment, when weighed against their incurred cost of operation. The utility function that dictates this cost is elaborated upon in Section 4, mainly depending on the scarcity and quality of the resource to be used.

In assessing the value and contribution of a resource, we take into consideration the 6 attributes presented in [3]. Namely, the functional capabilities of the resource (e.g., taking pictures, video), the levels of operation for each of them (e.g., resolution, frame size), power consumption for each level, the duty cycling scheme of the governing node, the region in which the resource operates (coverage) and finally its current location. These are shared attributes whether or not the resource is static or transient. In the latter case, more attributes are to be calibrated to evaluate the viability of considering a given transient resource in the ReP, and accordingly the cost factor of soliciting its services.

3.2.1 The abundance of transient resources

Transient resources, ones which pass by the deployment/interest region in the WSN, gain value via their pervasiveness and functional capabilities. To formally elaborate on the utility of



Figure 1 - Distinction between static and transient nodes in the O-WSN paradigm

transient resources, and their specific attributes, a formal definition is first presented as follows:

Definition 2: A transient resource extends a resource (Definition 1) as one with varying spatial and temporal properties. It lingers in the vicinity of the WSN for a deterministic **sojourn time**, during which it is of potential utility to the Resource Pool (ReP). The term "transient" reflects the limit on the duration this resource could be visible/utilized by functional requests.

We note that transient resources are quite abundant. In an urban setting, transient resources are seen in high-end vehicles, tablets and smart-phones, mobile weather stations and industrial sensors deployed by different proprietaries. Governed by their sojourn time and mobility models, we introduce the effective connectivity point/region and cost function associated with the use of its functionalities.

3.2.2 Spatial properties

Attributing a location to a transient resource is a difficult problem. Despite the extensive literature on localization for both static and moving nodes, the common issue is the overhead of multilateration required to accurately estimate a node's position. While adopting a crude metric for location would often suffice, we aim to identify a contact zone of each transient resource. That is, if we can communicate with it and identify it within a given region, then its resourcefulness would be tied to that region, until it leaves it.

In our model we assume that transient resources have a direct communication link with their local Arbitrators. That is, they are within communication range in a single hop. This facilitates a faster exchange of resources and cost functions within the short sojourn time; thus yielding higher utilization of its resources. This assumption is supported by the rapid deployment of higher end nodes which can take over the task of the Arbitrator, or present themselves as proxies to enable wider reach for the Arbitrator.

3.2.3 Temporal properties

A major property of a transient resource is the constrained time in which the network could utilize its functionalities. This is attributed to physical disappearance from the network region, or a duty cycling property that is contingent upon its own operational mandate. We highlight two important factors to calibrate the utility of a transient resources over the time dimension.

3.2.3.1 Sojourn time

Is a duration, in milliseconds, in which a resource maintains its attachment to the WSN at hand. This directly depends on the method adopted for determining location in the paradigm, yet is beyond the scope of this work. For example, if we consider the connectivity degree coupled with a hop-count as the indicator of a node's location, then *sojourn time* is defined as the span of time in which this aggregated metric of location is maintained. Thus, to ground sojourn time to an anchor, we define it as

Definition 3: Sojourn time of a transient node \mathbf{n}^T is the duration in which it resides in the vicinity of the current governing arbitrator.

We further note that sojourn time of a given transient resource is solely *effective* when coupled with availability, hence we expand into the notion of resource duty cycling.

3.2.3.2 Resource duty cycling

It is important to note that transient resources belong to devices that are inherently non-WSN nodes. That is, a luminosity sensor or a transceiver on a passing smart-phone, are already engaged in the applications of the home device and might not be available for utilization by the arbitrator at all times. Thus, it is important to note that only considering the sojourn time of such resources is insufficient. We instead consider the resources' *effective time*. Accordingly, a transient resource is viable when its duty cycling schemes is known. This could be represented via a pre-identified duty cycling schedule, or simply a timer of remaining milliseconds in operation in the vicinity of the current arbitrator.

In O-WSN, a viable transient resource would declare, upon its entry into the vicinity of an Arbitrator, its sojourn time and duty cycling pattern. Moreover, its trajectory and location(s) are relayed to the Arbitrator based on the mobility model of the transient node.

4. ELASTIC INCENTIVE SCHEMES

A core premise of the O-WSN paradigm is that future deployments of WSNs would converge towards functional diversity and cooperation, lowering the cost per node and maximizing the resource pool over nodes across networks.

The premise we need to justify, however, is the exchange of benefits. That is, "why would a transient resource (of a device) offer its resources in the first place"? since offering a resource for use by another network would entail energy, coordination, communication and potentially internal request-latency, it is important to caliber the impact of offering such a resource. In short, metrics that quantify how much a SN would be impacted by carrying out a specific task.

Although this topic delves into an already established literature on incentive schemes and rewarding "socially positive" behavior by arbitrary nodes, we highlight two important factors. First, in a heterogeneous network it would be farfetched to assume collusion free and socially-favorable behavior of nodes as they contribute their resources for the network they join. Second, establishing a fixed method that stresses equated contributions would facilitate a benchmark for assessing the valuation of each resource as it is offered for the network.

We thus focus on the two most intrinsic factors that dictate the value of a resource. The first is a proportional influence by remaining energy reservoir. That is, the more energy the node can sustain for a given operation, the more likely (and inversely the less it would valuate) it would contribute its resource. This scheme is detailed in Section 4.1. The second method is a sheer relationship to resource scarcity. That is, a higher abundance of that resource would result in a lower valuation at the current round. This approach is elaborated upon in Section 4.2.

4.1 Asymptotic Sigmoidal Pricing

We employ a static scheme for assigning cost units to utilizing a resource. That is, carrying out a functional requirement $f_{i,m}$ on a given node n_i at any given round τ_k depends on the energy impact of utilizing that resource. This takes into consideration two main factors. The normalized (w.r.t. to maximal battery power of node) indicator of energy depleted at n_i at the time of its use, denoted as ϵ_i and the maximal cost (asymptotic limit) for how much a resource could valuate to, denoted as C_r^{max} . Thus, aggregating these values would determine the total cost C_r for a resource **r** by using the asymptotic *Gompertz* function [7]

$$\boldsymbol{C}_{\boldsymbol{r}} = C_{\boldsymbol{r}}^{max} * \boldsymbol{e}^{\varrho * \boldsymbol{e}^{-s_{\boldsymbol{r}} * \boldsymbol{\epsilon}_{\boldsymbol{r}}}}$$
(1)

We chose the Sigmoidal Gompertz function due to its controlled increase in pricing of a resource, based on three important factors. Namely, the cap on valuation dictated by C_r^{max} , the flexibility to set a starting valuation by varying the Y-axis intercept dictated by ϱ and finally controlling the rate of increase in resource valuation based on the slope dictated by s_r . Thus, the cost function demonstrates significant sensitivity to remaining energy reservoir as it gets depleted, yet it never reaches C_r^{max} which is set by the arbitrator. This growth and its derivative are depicted in Figure 2. The green line demonstrates the growing cost function and the grey line shows the gradient of increase; diminishing as the function approaches the asymptotic limit.

4.2 Elastic Pricing – Impact of scarcity on price

This approach accounts for scenarios where the abundance of a resource dictate its cost to the network. The dynamics of functional gain depend on the availability of resources and the costs associated with each, and the willingness of the application to pay for a resource to carry out the functional requirement. Thus, it is imperative to include a scenario for "open markets" where a resource would probe a local arbitrator to offer its resources for a monetary reward.

To capture the essence of this approach, which is resource offerings made by transient resources, we present a cost function built upon two main factors. The resource offered, and its market valuation based on abundance. We assume that each arbitrator B_{α}



Figure 2 - Growth of the cost function in relation to depleting energy following the *Gompertz* model

is aware of the resources available in its vicinity, and can identify the density of each class of resource.

Accordingly, the arbitrator can dictate the valuation of a given resource as V_r

$$V_r = \frac{C_r}{|\Theta_r| * \alpha_r * \hat{C}_r}$$
(2)

Where \hat{C}_r is the normalized network valuation of resource C_r . However, the impact of this valuation on the elastic pricing of C_r is subject to a weighted factor α_r .

It is important to account for both factors when determining a price, especially for a transient resource. If there is only a single resource that would deliver a given functionality, then a "market valuation" has to be incorporated in its price to determine the need for it. For example, a camera pointing at the door of a grocery store might not strike great value until an incident exists around the store for which its utility rises.

4.3 On maximal matching and construed equality between resource providers

The mapping problem has to cater for transient resources to utilize them in time; thus only real-time solutions are viable. Time bottlenecks, cost constraints and system resilience are presenting major obstacles. Thus, we present a model to cater for dynamic assignment of resources to functional requests, yet now catering for rapid changes in locations, sojourn times and responsiveness. The remainder of this section details the system model, built upon the O-WSN paradigm to address these issues, and how the system adopts a dynamic heuristic to find the best possible match of functional requests to ReP constituents.

4.4 System model

We adopt a novel view of scalability, coupling the definition with functional coverage, rather than the number and distribution of sensing nodes. We envision wirelessly-enabled devices that did not belong to WSNs to aid and extend "functional scalability".

We represent the WSN network as a weighted bipartite graph, with resources and functional requirements creating two mutually exclusive sets of vertices. This formulation is depicted in Figure 3. The network is partitioned into sub-networks, each centered around the Arbitrator that handles the local ReP and functional requests to be made over its physical region. This partitioning allows for a rapid assignment of resources to functional requests, and remedies the significant variance between sojourn times and localities of transient resources over the whole network region. Thus, we represent the network as a graph G = (V, E), where

$$V = V^R \cup V^F \tag{3}$$

and V^R represents all polled resource instances in the current vicinity of the arbitrator, and V^F includes all the atomic functional requests of the applications to run in this vicinity. The weighted edges are defined as

$$E = \{ \forall e_{u,v} \mid \exists u \in V^F \land v \in V^R \land u. type \\ \equiv v. type \}$$
(4)

where the type matching indicates that the resource identified by node v meets the functional requirements of request represented by node u. This includes both static and dynamic requirements; i.e., the 6 core attributes highlighted in Section 3.2 in addition to spatial and temporal properties induced by transient resource attributes if $v \in n^T$.

The value of an edge $e_{u,v}$ represents the cost of utilizing resource v, is computed as

$$\boldsymbol{e}_{\boldsymbol{u},\boldsymbol{v}} = \boldsymbol{\kappa}(\boldsymbol{v}) \tag{5}$$

where the cost function denoted as $\kappa(v)$ is computed according to the utility function explained in Section 4.2.



Figure 3 - Maximal bipartite matching of resources to functional requirements

4.6 Dynamic rounds – Capturing transient resources

The dynamic nature of transient resources dictates a fine tuned operation scheme that caters for their varying linger times. As highlighted in motivating the use of local arbitrators, the variance of spatial, temporal and mobility properties across transient resources introduce a significant impact on catering for their utilization. That is, short round times could deem many "slower" resources useless to the network, or incur significant control overhead in their discovery and utilization, and longer round times would impact the discovery rate of "faster moving" resources or ones with shorter duty cycles. Thus dynamic rounds are an intrinsic property of the O-WSN paradigm to cater for transient resources.

We define network operation in terms of rounds, τ_t . Each τ_t could vary in duration, yet constitutes three main phases. The first phase τ_t^{setup} addresses the setup phase in which the local ReP is built, and functional requests are aggregated over all applications in the arbitrators vicinity. The second phase, τ_t^{map} involves the mapping time during which minimum cost mapping of $V^F \to V^R$ takes place. The final phase in each round, $\tau_t^{operational}$ is when the network actually operates to fulfill the functional requests per the matching mandate dictated during τ_t^{map} .

At each round, the durations of τ_t^{setup} and τ_t^{map} do not change. The former has a time out period during which all functional requests have to be reported by all $a_j \in A$ and all nodes willing to participate report their aggregated resource sets R_i and cost of utilizing each, i.e., $\kappa(v)$. The latter duration τ_t^{map} is the running time of the mapping algorithm, elaborated upon in Section 4.6.

However, the duration of $\tau_t^{operational}$ would vary each round and is impacted by all $\nu \in n^T$. That is, we introduce the notion of resource *effective time* in the vicinity of the current arbitrator, indicating the duration for which a transient resource ν would be an active member of the arbitrators current ReP. We thus denote the *effective time* of a transient node ν with a duty cycle percentage of ν_{DC} and sojourn time of ν_{st} as ν_{et}

$$\boldsymbol{v}_{et} = \boldsymbol{v}_{st} * \boldsymbol{v}_{DC} \tag{6}$$

There are different methods for assessing the impact of transient resources on the duration of a round. For example, the network could reassess every time a transient resource leaves the network, thus creating a void, or whenever a new one is expected to enter (according to the mobility models known a priori and the interconnection between arbitrators).

However, we note the motivation behind this work as maximizing functional gain while utilizing current resource pools. The notion of re-invoking a matching algorithm every time a transient resource is introduced contradicts the stability of network operation. Thus, we depend on a tunable duration time to utilize as many, not all, transient resources.

From a functional perspective, transient resources are of higher viability when they introduce one of two edges: (1) A scarce resource that the ReP is shy of, or (2) a cost reduction that significantly reduces the cost for meeting functional requirements of current set of A.

We hereby introduce a dynamic function that assesses the impact of transient resources on round duration $\tau_t^{operational}$ is explained in Equation (7)

$$\tau_{t}^{operational} \propto \sum_{v \in n^{T}} v_{et} \\ * \left(\omega_{f} * \frac{1}{|\Theta_{v}|} + \omega_{c} \right) \\ * \frac{\overline{\kappa(\Theta_{v}) - \kappa(v)}}{\max(\kappa(\Theta_{v}))}$$
(7)

where $|\Theta_{\nu}|$ is the number of resources in the current ReP of a matching type to ν and $\overline{\kappa(\Theta_{\nu})}$ is the average cost requested by resources of type ν to contrast with the maximum cost requested for resources type ν denoted as $max(\kappa(\Theta_{\nu}))$; as a normalization factor. To cater for a fine tuned operation of O-WSN that could favor one impact over the other (depending on the design goals of the network practitioner), we introduce impact weights for functional and cost impacts, as ω_f and ω_c respectively. We highlight that $0 \leq \omega_f, \omega_c \leq 1$ and are set by the arbitrator.

4.7 Utilizing the Hungarian method

The formulation of the O-WSN model as a bipartite graph under a cost function for each resource instance, i.e., each edge with a matching as described in Equation (4), lends itself to the significant literature on maximal bipartite matching. There is a wealth of algorithms that address the issue of finding an optimal matching between V^R and V^F . We adapt the maximal bipartite matching algorithm developed by H. Kuhn commonly referred to as the Hungarian method [8]. It is a polynomial time algorithm, which is computationally tolerated in our model since it would run independently on local vicinities of Arbitrators. A more thorough discussion of the assignment problem, and the use of the Hungarian method adopted in this work, are detailed in [9].

5. PERFORMANCE EVALUATION

The performance evaluation for RR-WSN adapting to transient resources is carried out in MATLAB. We set up an experiment with variable number of nodes, both static and transient, and adopt a dynamic assignment scheme of functional requirements for each run. The locations of nodes follow a uniform random distribution over the deployment region. We run our simulation models with different energy levels for sensing nodes, to fall randomly in the range of 80% to 100% of an initial battery power set to a maximum of 3 kJ. Transient nodes also start with a random battery level in the same range, with an upper limit of 5 kJ (as dedicated for O-WSN). We assume that transient nodes hold a vastly heterogeneous pool of resources [10], and static sensing nodes have a more homogeneous pool. In our experiments we assume static sensing nodes have an arbitrary number of resources from the set of {'Temperature sensor'; 'Light sensor'; 'Micro controller'; 'Memory'; 'Transceiver'; 'Camera'; 'Radar' }. Transient resources could have any of these resources, in addition to a more smartphone oriented pool of resources that we abstract as {'GPS' ; 'microphone' ; 'geomagnetic'; 'barometer' }. Naturally, each node holds a transceiver, micro controller and one type of sensor as a minimum. Even indoor networks hold a significant abundance of such resources [11].

The impact of transient resources on network performance is complex. On one hand, they leverage functional requests and aid energy-deprived sensor nodes. On the other hand, they incur



Figure 4 - Transient nodes leveraging network performance over rounds

significant costs to the owner of the static nodes as they charge for carrying out the tasks. We next examine the operation of O-WSN aided with transient resources, over a number of dynamic rounds. Figure 4 depicts O-WSN operation with 60 static nodes, for 50 rounds, on a typical region for an arbitrator of size 100 x 100 m. Each round has a $\tau_t^{operational}$ duration of 5000 sec in addition to a variable round time in the range of [0,5000] dependent on the impact of transient resources, as per Eq. 7. transient resources have a random effective time v_{et} in the range [500,1500], and arrive according to a Poisson process with average 1000 seconds.

The network significantly depends on static resources with lower cost incurred for functional tasks at the earlier rounds. However, due to the relative pricing of resources dictated by the Gompertz model, in Eq. 1, over later rounds, it becomes more cost effective to depend on transient resources. An interesting phenomena occurs after approximately 20 rounds, when energy reservoirs at both static and transient nodes start witnessing equal depletion, hence the uptake of resources from both classes of resources grow in a balanced pattern.

However, it is important to note the impact of another factor, which is the growth scaling factor S_r highlighted in Eq. 1 following the growth model depicted in Figure 2. In Figure 4, both static and transient nodes share an equal S_r value of -0.05, since it has the steadiest increase in resource valuation. Mean time to failure and Network resilience

Failures happen. However, the definition of a failure varies significantly across different WSN paradigms. A common metric of interest is the mean time to failure (MTTF) of nodes, and that of the network. That is, how long does it take the network, on average, to fail? We cannot generalize failure to encompass any node that has failed (ceased to operate) in the network. It is critical to understand that failure's impact on network operation; since it could very well occur without disturbing network operation. This is mostly evident in dense networks.

In RR-WSN we define network MTTF as the time (from deployment) until the first functional request could not be satisfied. Accordingly, MTTF is not affected by the failure of a resource unless it is irreplaceable in its field of operation. A resource r_i is replaceable if another resource r_j exists within the same fidelity region served by r_i and has the capacity and



Figure 5 - Impact of Duty cycling of SNs on MTTF of network under O-WSN

attributes to serve the functional requests previously assigned to r_i as per the definitions in Section 3.2.

In O-WSN, it is important to note the impact of static resources on MTTF. While transient resources offer a dynamic ReP, there are no guarantees in terms of sustained functional matching for the duration of the network. Thus, it is important to sustain network functionality via static nodes. However, increasing static resources is a constant overhead. Moreover, increasing resource availability (via increasing duty cycling time) has an impact on cost of running the network. In Figure 5 we depict O-WSN operation under static resources only. This experiment was designed to measure the impact of duty cycling static resources to match functional requirements, until network failure. The MTTF is shown as the last point on each respective curve. Evidently, increasing duty cycling time has an impact on cost of running functional requirements, thus the differentiated increase depicted for each simulation at any given round (common until the first 6 rounds. It is important to note this experiment was run under varying nodal locations, and energy reservoirs, yet with a fixed total energy value across all static resources. The experiment was run with 50 static nodes, in a 100 x 100 m area, each node having a combination of 4 resources, two of which are a transceiver and an MCU. The experiment was setup to enforce 100 functional requirements that are static over the rounds, i.e., the functional requirements did not change in attributes.

Under this experiment, it was also shown that MTTF is negatively impacted by increasing duty cycling time, as nodes consume more energy in each round, resulting in a quicker battery depletion. Thus, network failure occurs sooner (at earlier rounds) as we increase duty cycling of static nodes. It is important to note that survivability of the network over rounds is manifested in longer network lifetime. Introducing transient resources in O-WSN operation impacts our definition of lifetime, and inherently MTTF. At any given point, even if static resources fail to meet functional requests, transient resources offer a pool of resources that aid in meeting the requests.

We also note the resilience of O-WSN in recovering from static resource failures, and the utility of transient resources when more static resources fail. This transient property makes for an alternating but sustained performance, as depicted in Figure 6. where the same experiment was repeated, yet with a varying rate of arrival for TNs. We simulate a scenario where TNs arrive according to a Poisson process, with an average arrival rate of 10 TNs per round. More TNs are utilized as they preserve higher energy reservoirs, thus increasing the network cost of carrying the same functional requirements.



Figure 6 - The utility of transient nodes in maintaining O-WSN resilience, under a Poisson arrival process with average 10 TNs per round

6. CONCLUSIONS AND FUTURE WORK

Current practices for designing and deploying Wireless Sensor Networks (WSN) persistently yield application specific networks. Such limitation in applicability has thus far been driven by a basic tradeoff between functionality and resource availability – a tradeoff that has received great research attention over the years [12]. O-WSN parts from this traditional model and offers a new WSN approach that decouples application considerations from network architecture and protocol.

This paper introduced the O-WSN paradigm. The goal was to reduce the cost impact of running multiple functional tasks, on an ever-changing base of resources that are wirelessly accessibly [13]. Significant parameters of O-WSN were developed to cater for a varying rate of arrival of transient resources, and their volatile availability in network vicinity. Moreover, it was important to devise cost functions that resemble the willingness of both static and transient resources to cater for functional requests. Normalized operation mandated that all nodes be held to a common metric of arbitration, which is the cost in O-WSN.

We adopted the *Gompertz* model of growth, whereby an increasing exponential function would map the stringency of power at a resource to the valuation of utilizing its resource. The *Gompertz* function allowed for a flexible growth scaling via tunable parameters, and sustained an asymptotic limit (cap on possible valuation) that enables a more viable contribution of resources to the functional resource pool (ReP).

O-WSN promises a great potential for realizing a truly large-scale WSN unity that alleviates resource waste in redundancy, and delivers maximized utility for required applications. As future work, more investigations are required to determine the viability, gain and energy-efficiency of adopting a partial-allocation scheme in O-WSN. While it could be a communication waste to spend considerable overhead in partitioning a functional request to allow for multiple assignments, yet the possibility of not finding a sufficient ReP deems this an important point to investigate.

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