Routing using Hidden Markov Model and Energy Efficient by Particle Swarm Optimization with Wireless Network Interface Selection for Industrial Mobile Devices

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Abstract
Now a day, Mobile devices like Personal Digital Assistants (PDAs) and smart phones are generally used in our day to day lives and as well in numerous industrial areas. Normally, these mobile devices comprising several wireless network interfaces for instance 3G, Bluetooth and Wi-Fi, which are designed to utilize multiple channel. The available network capacity can be increased by using channels with wireless network interfaces, but this requires the development of new methods for energy reduction problem. Since, substantial quantity of energy is utilized to transmit the data via wireless communication, this problem is solved by using proper selection of network interface proficiently with the purpose of prolonging the life span of mobile devices and their applications. In case of the industrial areas, modifications in the communication environment are critical by reason of substantial noise sources, as a result of inadequate energy and because of distortion in the transceiver circuitry of strong motors, electrical discharge devices, and static frequency changers, etc.

With the aim of resolving these issues, present a novel routing and energy-efficient Adaptive Wireless Network Interface-Selection scheme (AWNIS) with Particle Swarm Optimization (AWNIS-PSO) is specifically designed for industrial mobile devices. Discover route optimization methods in wireless network interface selection: 1) choosing the most conservative energy consumption and data transfer delay patterns to guarantee timely transmission, and 2) searching detouring paths by using Hidden Markov Model (HMM) while the energy level of a relay node is very less to utilize the required interface, which promises well-timed delivery.

cThe intention to attain data delivery with packet whilst reducing energy utilization at every node, data transfer delay patterns and additionally extending the network lifespan by choosing economically effective relay nodes and wireless interfaces. Searching detouring paths by using HMM is performed based on the probabilistic mathematical modelling to extend the network lifetime.

Simulation outcomes prove that the presented AWNIS-PSO scheme entirely exploits the provided Packet Delivery Ratio (PDR) to preserve energy utilization by choosing the interface, and dispersing network traffic over the network. Presented AWNIS-PSO scheme achieves reliable PDR failures and energy effectiveness when assuring some level of data transfer delay.

Index Terms: Energy Efficiency, Industrial Mobile Devices, Mobile Devices, Smart Phones, Wireless Network Interface Selection, Routing, Multiple Channel, Hidden Markov Model (HMM) and Particle Swarm Optimization (PSO).

Introduction

Recently, wireless technologies are broadly utilized in numerous industrial areas, since wireless technologies present numerous profits to businesses, with mobility, flexibility, and cost savings as they don't require wired connections [1], [2]. In industrial units, stationary systems could be linked over a wireless network to mobile subsystems or robots for improved connectivity [3]. Besides, wireless technologies could make it very simpler to get into plant machinery for the purpose of diagnostic or programming [4]. Mobile devices for instance personal digital assistants (PDAs) and smart phones could be utilized to regulate and observe machinery [5].

Mobile devices are utilized for exchanging the information amongst workers. It also contains numerous wireless network interfaces for instance 3G, Bluetooth and Wi-Fi. Every wireless network interface contains moderately diverse features in regard to its energy utilization, data transfer rate, service area and other aspects [6]. 3G networks contain broader service areas and utilize superior receive/transmission energy than Wi-Fi networks [7]. Usually, a Wi-Fi access point could cover a radius of around 100 200 m. 3G utilizes nearly twice as much energy as Wi-Fi to transmit the data [6]. Fourth Generation (4G) mobile system will be set going in a few years. From the viewpoints of the users, the features of the 4G network systems will include high usability, higher energy efficiency, higher battery usage to support for multimedia services at low transmission cost, personalization, and integrated services.

However, the battery depletion problem still remains the biggest drawback of the electronic world in general; and smart phones/wireless devices in particular. There are quite a few default energy saving techniques in iPhone and smart phones which allow the user to adapt certain application layer functionalities. For example, use of an on device light sensor to monitor the ambient light and lower the display brightness. Another example is to manage CPU-intensive background applications. However, these techniques do not provide any step-wise change and real-time change in the energy consumption and is an inherent limitation of the system. Many studies have been proposed to enhance energy efficiency in a variety of way.

Several studies were conducted for enhancing and expanding the operating time of mobile devices by leveraging various network interfaces [8]. With the aim of devising effective wireless network interface management techniques, numerous factors have to be taken, for instance the signal strength, the data transfer rate, and the kinds of existing network interfaces. In preceding researches, the link quality in keeping with the signal strength, the data transfer rate, and the wireless network interface-selection interval were not taken con currently. The network interface-selection interval is a significant spect as the network connectivity cost of verifying existing wireless network interfaces is substantial and the accessibility changes in keeping with the network environment. So, an effective network interface management technique is needed to improve energy efficiency in industrial areas and identifying the route to share information turn out to be significant.

In this research, take up an industrial mobile device, which is fitted out with two wireless network interfaces: Wi-Fi and 3G. Dependent upon Hidden Markov Model (HMM) mathematical modeling, examine the energy utilization of the mobile device when taking the data transfer rate and the energy cost of data transfer in keeping with the network interface-selection interval. Furthermore, examine the data transfer delay of three diverse network interface- selection policies: by utilizing 3G only, Wi-Fi only and both 3G and Wi-Fi. Dependent upon the investigation outcomes, present an energy-efficient Adaptive Wireless Network Interface-Selection scheme (AWNIS) with Particle Swarm Optimization (AWNIS-PSO) technique. It takes the link quality and acclimates a dynamic network interface-selection interval by estimating the present network environment. After the probability values are found from HMM, present a route selection technique, which takes energy availability in nodes while creating route decisions. The simulation outcomes prove that presented AWNIS-PSO technique efficiently progresses the energy efficiency when assuring some level of data transfer delay.

Related Work

In [9] present a comprehensive analysis of real smartphone usage during a 6-month study of real user activity on the Android G1 smartphone. The goal is to study the high-level characteristics of smartphone usage, and to understand the implications on optimizing smartphones, and their networks. Overall, present 11 findings that cover general usage behavior, interaction with the battery, power consumption, network activity, frequently-run applications, and modeling usage states. Cool Spots enable a wireless mobile device to automatically switch between multiple radio interfaces, such as Wi-Fi and Bluetooth, in order to increase battery lifetime. The contribution of this work [10] is an exploration of the policies that enable a system to switch among these interfaces, each with diverse radio characteristics and different ranges, in order to save power - supported by detailed quantitative measurements. The system and policies do not require any changes to the mobile applications themselves, and changes required to existing infrastructure are minimal. Results are reported for a suite of commonly used applications, such as file transfer, web browsing, and streaming media, across a range of operating conditions. Experimental validation of the Cool Spot system on a mobile research platform shows substantial energy savings: more than a 50% reduction in energy consumption of the wireless subsystem is possible, with an associated increase in the effective battery lifetime.

In [11] formulate the selection of wireless interfaces as a statistical decision problem. The key to attaining the potential battery improvement is to accurately estimate Wi-Fi network conditions without powering up its network interface. We explore the use of different context information, including time, history, cellular network conditions, and device motion, for this purpose. We consequently devise algorithms that can effectively learn from context information and estimate the probability distribution of Wi-Fi network conditions. Simulations based on field-collected traces show that our algorithms can improve the average battery lifetime of a commercial mobile phone for a three-channel electrocardiogram (ECG) reporting application by 39%, very close to the theoretical upper bound of 42%. Finally, our field validation of our most simple algorithm demonstrates a 35% improvement in battery lifetime.

In [12] energy costs for transmitting a given amount of data on these wireless interfaces can differ by an order of magnitude. On the other hand, many of these applications are often naturally delay-tolerant, so that it is possible to delay data transfers until a lower-energy Wi-Fi connection becomes available. Present a principled approach for designing an optimal online algorithm for this energy-delay trade off by utilizing the Lyapunov optimization framework. SALSA could mechanically acclimatize to channel conditions and requires only local information to decide whether and when to defer a transmission. Evaluate SALSA using real-world traces as well as experiments using a prototype implementation on a modern smartphone. Experimentation results show that SALSA can be tuned to achieve a broad spectrum of energy-delay tradeoffs, is closer to an empirically-determined optimal than any of the alternatives compare it to, and, can save 10-40% of battery capacity for some workloads.

Presents a new activation service is proposed [13] to reduce the energy consumption in mobile phones. The basic idea behind this proposal is to introduce an auxiliary receiver, which is capable of receiving a special signal from the access point and actuate the wireless interfaces on the mobile phone. During idle times, the wireless interfaces are switched off to reduce its idle power - the energy a device consumes in `standby' state. When call or data arrives, the auxiliary receiver will receive notification from an access point and actuate the relevant wireless interface on the mobile phone to receive the data or call.

In [14] argue that simple "bandwidth aggregation" approaches do not provide any meaningful benefits when the multiple interfaces used have highly disparate bandwidths as is true in many practical environments. Then present super-aggregation, a set of mechanisms that in tandem use the multiple interfaces intelligently and in the process is able to achieve a performance that is "better than the sum of throughputs" achievable through each of the interfaces individually. Prototype super-aggregation on both a laptop and the Google Android mobile phone and demonstrate the significant (up to 3x throughput) performance improvements it provides in real-world experiments.

In [15] propose Catnap, a system that reduces energy consumption of mobile devices by allowing them to sleep during data transfers. Catnap exploits high bandwidth wireless interfaces -- which offer significantly higher bandwidth compared to available bandwidth across the Internet -- by combining small gaps between packets into meaningful sleep intervals, thereby allowing the NIC as well as the device to doze off. Catnap targets data oriented applications, such as web and file transfers, which can afford delay of individual packets as long as the overall transfer times do not increase. Evaluation shows that for small transfers (128kB to 5MB), Catnap allows the NIC to sleep for up to 70% of the total transfer time and for larger transfers, it allows the whole device to sleep for a significant fraction of the total transfer time. This results in battery life improvement of up to 2-5x for real devices like Nokia N810 and Thinkpad T60.

Proposed Routing and Energy-Efficient Adaptive Wireless Network Interface Selection Methodology: In this part, describe the data-transfer energy cost and examine the energy utilized by a mobile device in keeping with the network interface-selection interval. In addition examine the data transfer delay of the three aforesaid network interface-selection policies: by utilizing 3G only, Wi-Fi only and both 3G and Wi-Fi. Dependent upon the investigation outcomes, present an energy efficient Adaptive Wireless Network Interface-Selection scheme (AWNIS) with Particle Swarm Optimization (AWNIS-PSO) assignment strategy, which takes the network state and utilizes a dynamic network interface-selection interval for improving the energy efficiency of data transfers. Proposes, energy efficient AWNIS-PSO assignment strategy that simplifies coordination among nodes, while utilizing multiple channels, and is well-suited for wireless network. The objective of proposed Hidden Markov Model (HMM) technique is to reduce energy utilization at every sensor node and extend network lifetime while delivering data packets from a source node to a target node, when fulfilling the packet deadline restraint. Every sensor node is static and is set up with multi interfaces, for instance, Wi-Fi and 3G.

A sensor node could find where to relay (i.e., next-hop) the received data packet and via radio interface. A higher-energy radio interface (e.g., Wi-Fi) would utilize lot of energy, however could transfer farther and sooner when matched up with a lower-power radio interface like 3G.

Consider data delivery applications under delay constraints. Effectively, HMM method diversifies route paths in the network with the purpose of extending the entire network life-time. Identify another path for robust data delivery beforehand the route path breaks because of energy diminution. Utilize the distance-vector algorithm since the underlying routing technique.

System model

Consider an industrial mobile device, which is fitted out with more wireless network interfaces with lot of sensor nodes. According to this assumption, could utilize the finest network interface from amongst numerous wireless network interfaces by taking its energy cost. Describe an easy data-transfer energy model for wireless data transfer. Model the data-transfer energy cost with the cost of setting up a connection and transmitting megabytes data, in this manner:

$$E(i) = E_e(i) + n \times E_t(i) \tag{1}$$

The data transfer cost of the i^{th}th network interface could be computed by the sum of the network set up cost and the energy cost for transmitting megabytes, as in (1). With the purpose of enhancing the energy efficiency and decreasing the amount energy utilization, it is essential to select the smallest costly network interface since the network interface for data transfers upon every instance of network interface selection. Every route selection techniques considers as an input the packet delivery deadline R, and the time D and transmission energy E via every interface $i \in \{1, \dots, M\}$(where M is the amount of available interfaces). D and E are vectors of size M, and are initialized in rising order of transmission energy (i.e., $D_1 > D_2 > \cdots > D_j > \cdots > D_M$and $E_1 < E_2 < \cdots < E_j < \cdots < E_M$). Every sensor node contains topology information for every interface type *i* (*Topology*) and could compute the shortest path amid source and destination. For performing this, a sensor node uses Dijkstra's algorithm, in which every edge amid nodes in the topology is weighted with the Expected Transmission Count (ETX) [16] as per-hop cost via the equivalent link. Taking this information, every node alongside the path creates a local routing decision to choose interface and subsequent hop with the aim of meeting the packet delivery deadline when decreasing the entire power utilization in the system.

Data-transfer energy cost modelling with 3G and Wi-Fi network interfaces: So as to design the data-transfer energy cost with numerous wireless network interfaces, take upan industrial mobile device, which is fitted out with a principal wireless network interface and a substitute wireless interface, for instance, a Smartphone. The mobile device could connect and transmit data via a less-power and higher-availability preliminary wireless network for example 3G that gives a less data transfer rate and utilizes more data-transfer energy when matched up with a substitute wireless network.

Or else, another wireless network merely exists in restricted areas, such as Wi-Fi. Another wireless network interface offers a high data transfer rate and utilizes less data-transfer energy compared to the principal wireless network. For another wireless networks, the finest quality access point is chosen to link and transmit the data amongst multiple access points. While the device links to another wireless network, the connection via principal wireless network is detached. Identical suppositions could be identified in previous research [11-12] and [17]. Commonly, these suppositions are sensible as principal wireless network interfaces for instance, 3G are utilized to transmit data by interacting with a comparatively distant base station, normally a 3G base station. With the purpose of enhancing the data transfer rate and energy efficiency, another wireless network interfaces for instance, Wi-Fi are utilized to transmit data by conversing with a comparatively close base station, for example, a Wi-Fi access point. Preliminary wireless network interfaces utilize more energy while transmitting data compared to another wireless network interfaces because of the long-range wireless communication. Therefore, principal wireless network interfaces offer less data transfer rates compared to another wireless network interfaces.

Considered that a mobile device could connect and transmit the data via a less-power and higher-availability principal wireless network for instance 3G. This supposition replicates the reality of 3G [11]. The accessibility of Wi-Fi is lesser compared to that of 3G and the usage of Wi-Fi is limited to the coverage of the specific access point [11] [12] [17]. Or else, the energy efficiency of Wi-Fi is superior to that of 3G in regard to the data transfer cost. Normally, 3G utilizes closely double the amount of energy utilized by Wi-Fi for the duration of a data transfer [6][18]. When Wi-Fi is existing rather than 3G in some areas must utilize Wi-Fi to decrease the energy cost of data transfers. With the aim of decreasing the energy utilization and data transfer delay, could utilize 3G as well as Wi-Fi interchangeably by taking the accessibility of Wi-Fi, as depicted in Fig. 1(a).

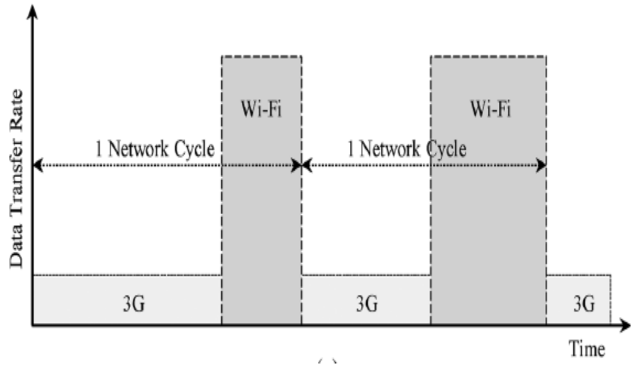

Figure 1: An Example of using Both 3G and Wi-Fi to Transfer Data

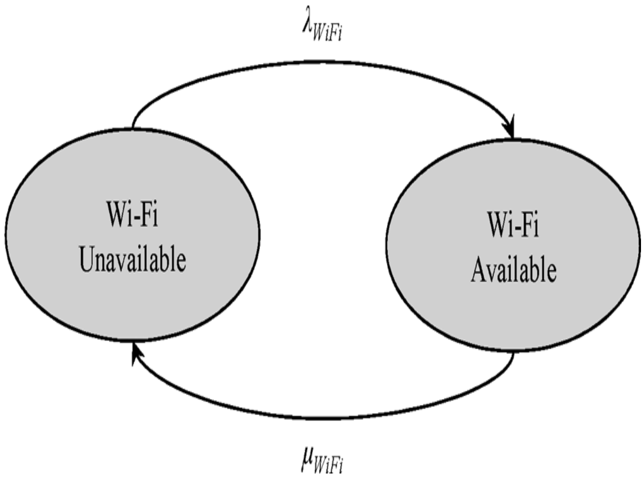

Figure 2: State Diagram of a Wi-Fi Network

Along with the abovementioned assumptions, could provide the status of Wi-Fi based on the accessibility of Wi-Fi, as depicted in Fig. 2. It displays a state diagram of a Wi-Fi network. At this point, signifies the state transition rate of Wi-Fi from the unavailable state to the available state.$\mu_{\mathrm{Wi-Fi}}$ is known as the state transition rate of Wi-Fi from the available state to the unavailable state. $\lambda_{\mathrm{Wi-Fi}}$ state transition rate of Wi-Fi from unavailable state to available state. Briefly, could design the usage patterns of 3G and Wi-Fi through a continuous Markov process [19-21]. $\mu_{\mathrm{Wi-Fi}}$ as well as$\lambda_{\mathrm{Wi-Fi}}$ couldmodify based upon the network environment, on the degree of user mobility, and on other factors, Examine the energy utilization of a mobile device by computing the energy utilization of one network cycle, as stated in (2). $TC_D$is called the entire energy utilized by a mobile device for the duration of one network cycle. The amount of energy utilized for the period of one network cycle is comprised of four major components: the energy utilized by 3G, the energy utilized by Wi-Fi, the energy utilized by the choice of the network interface, and the energy utilized by the handover amid 3G and Wi-Fi. The energy utilization amounts for 3G and Wi-Fi are mostly impacted by the amount of data to be transmitted and the data transfer cost persistent as the handover is carried out simply once for each network cycle. Consequently, the consequence of the handover cost on the total energy utilization is minor, and the vertical handover delay could therefore be decreased to closely zero as stated by the findings of previous research work [22-23]. Consequently, discover a manner to decrease energy utilization, in this way:

$$TC_{Device} = TC_{transfer} + TC_{NIS} + TC_{HO} \quad (2)$$

$TC_{transfer}$ total energy utilization of 3G and Wi-Fi for data transfer for the duration of one network cycle.

TC_{NIS} total energy utilization for network interface selection for the period of one network cycle.

TC_{HO} total energy utilization of handover between 3G and Wi-Fi for the duration of one network cycle.

If the average requested data transfer amount is comparatively small, so it isn't required to utilize Wi-Fi since the network detection cost, i.e., the cost of Wi-Fi scanning to search for an access point, is desirable. So, it is required to assume the amount of requested data to be broadcasted. $AR[t]$ represent the average requested data transfer amount (MB/s) in the t^{th} network cycle. $E[AR]$ Represent the expected average requested data transfer amount. e_{3G} and e_{Wi-Fi} represent the data-transfer energy cost of 3G and Wi-Fi per MB, respectively. The energy usage per second of data transfer by 3G and Wi-Fi are $e_{3G} \times E$ [AR] and , $e_{Wi-Fi} \times E\ [AR]$ respectively. The total amount of energy consumed for broadcasting the data while one network cycle can be computed as follows:

$$TC_{transfer} = e_{3G} \times E[AR] \times E[T_{3G}] + e_{Wi-Fi} \times E[AR] \times E[T_{Wi-F}] \quad (3)$$
$$= e_{3G} \times E[T_{3G}] + e_{Wi-Fi} \times E[AR] \times E[AR]$$

As described above, periodic wireless network selection is necessary to choose and connect to the more energy-efficient Wi-Fi network. Evaluate the total energy usage amount for the periodic wireless network selection as follows. Initially, know the number of network interface-selection events done in order to compute the total energy usage amount for network interface selection while one network cycle. Every network interface selection is a Bernoulli trial. The output of every network interface selection is either a success or a failure, as discussed previously.

The objective of proposed Hidden Markov Model (HMM) method is to minimize energy consumption at every sensor node and prolong network lifetime when transferring the data packets from a source node to a destination node, while satisfying the packet deadline constraint. The main motivation of Hidden Markov Model (HMM) work is to develop an efficient probabilistic method to measure the probability values that Wi-Fi and 3G is an available state after t seconds by the transient state probability of a continuous Markov process. Consider there are M-state such as available and unavailable of network with Markov chain of length N becomes number of input nodes for each network, and there are M^N possible sequences results are used to obtain whole TC_{energy}. total amount of energy with the packet delivery ratio constraints. However, it is clear that, when the state space of HMM is large or the sequences of HMM long, several of other sequences might be also interested to perform mixed pixel wise probabilistic estimation.

In general HMM regard as two kinds of state sequences such as hidden state and observed data state[24-25]. In hidden state both the Wi-Fi and 3G network are simultaneously either available or unavailable state .In observed state total energy consumption results of the both Wi-Fi and 3G network is determined for network selection. Let us consider a hidden state sequence $S = \{Wi-Fi_1, Wi-Fi_2, \dots .3G_1\}$ and the observed data sequence results becomes energy consumed results for each network. So, that hidden markov state sequence can evaluate the likelihood that Wi-Fi is an available state after seconds by the transient state probability of a continuous Markov process [26-27], as expressed in (4).

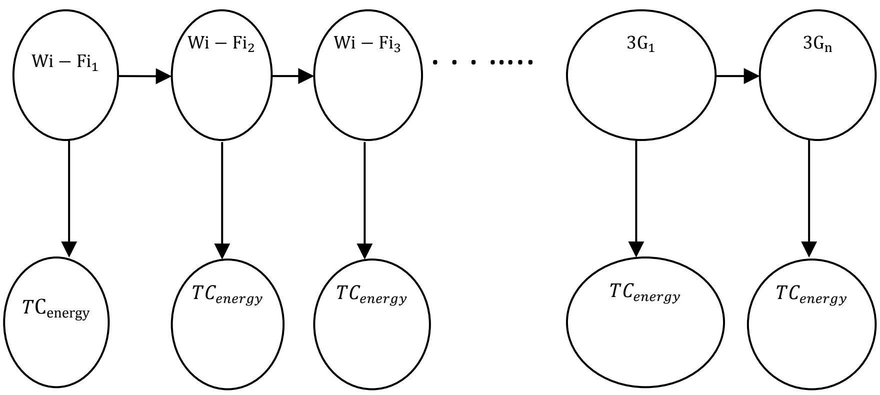

Figure 3: HMM Depicted as a Directed Graphical Model

$$P(Wi-Fi, \pi_0, E) = P(Wi-Fi_1 | \pi_0) \prod_{n=2}^{N} P(Wi-Fi_n | Wi-Fi_{n-1}, E) \quad (4)$$

$$P(Wi-Fi_1 is \text{ unavailable after t seconds} | \text{ unavailable} | \pi_0, E) = \frac{\mu_{Wi-Fi}}{\lambda_{Wi-Fi} + \mu_{Wi-Fi}} + \frac{\lambda_{Wi-Fi}}{\lambda_{Wi-Fi} + \mu_{Wi-Fi}} \times e^{-(\lambda_{Wi-Fi}+\mu_{Wi-Fi})t} \quad (5)$$

$$P(Wi-Fi_1 is \text{ available after t seconds} | \text{ unavailable} | \pi_0, E) = \frac{\lambda_{Wi-Fi}}{\lambda_{Wi-Fi} + \mu_{Wi-Fi}} - \frac{\mu_{Wi-Fi}}{\lambda_{Wi-Fi} + \mu_{Wi-Fi}} \times e^{-(\lambda_{Wi-Fi}+\mu_{Wi-Fi})t} \quad (6)$$

Here the initial stage results of hidden state are obtianed from initial probability vector π_0 so that $\pi_{0,m} = p(Wi-Fi_1 = m)$ denotes the probability of $Wi-Fi_1$ being in the state $m \in \{1, \ldots .. M\}$, whereas any subsequent network channerl state $Wi-Fi_n$ (with $n > 1$) is chosen based on transition matrix E ,consequently expresses the probability of moving from one state m to another state m' and it is defined as:

$$[E]_{m'm} = p(Wi-Fi_n = m | Wi-Fi_{n-1} = m') \quad (7)$$

For a specific path $Wi-Fi_n$ following the observed energy consumption results are generated separately according to,

$$p(TC_{energy} | Wi-Fi) = \prod_{n=1}^{N} p(TC_{energy_n} | Wi-Fi_n) \quad (8)$$

Where the densities $p(TC_{energy} | Wi-Fi)$ are often referred to as emission probabilities results for energy. One of the major problems occurs in the present HMM methods is that linear time effectiveness.

After the probability values were identified, need to suggest a route selection scheme which assumes the energy availability in nodes when creating the route decisions. Call this Energy-Aware Routing (EAR). Nevertheless, EARTR considers one extra step to verify if the chosen next hop has adequate energy to receive and broadcast the packet (lines 13-15 from Algorithm 1). If not, EARTR choose an alternative next hop from its neighbourhood. Algorithm 1 gives information for the choosing an alternative next hop. Initially, it is required to find entire immediate neighbours of current Node reachable through interface type j. Then compute the path and cost to destination through every alternative next hop candidates. Choose a random next hop candidate whose path cost (costNxt$_j$) is lower than the path cost of the present node (cost$_j$) (i.e., choosing a next-hop node closer to destination than the current node). The latter assures a loop-free route.

Algorithm 1: Energy-Aware Routing (EAR)

1. Input: cost$_j$, currentNode, dst, D, TC_{energy}
2. Output: Alternative next hop
3.
4. for all nodes n in INeigh do
5. for all interfaces j $\in \{1, \ldots, M\}$ do
6. [pathNxt$_j$,costNxt$_j$] = Dijkstra(nextNode, dst, TC_{energy},)
7. Select $\arg min_{j\in\{1,..M\}} TC_{energy}, . s.t\ N_j * D_j \leq R_{nextnode}$
8. $P_{txNextNode} = TC_{energy}$;
9. $P_{rxNextNode} = TC_{energy}$ {Next statement guarantees a loop-free route}
10. if costNxt$_j$< cost$_j$ and energy map[nextNode] < $P_{rxNextNode} + P_{txNextNode}$ then
11. neighbors = neighbors: Append(n)
12. end if
13. end for
14. end for
15. {Select a random alternative next hop from neighbors}
16. $altNextHop = SelectRandom(neighbors)$
17. return altNextHop

If Wi-Fi is accessible, Wi-Fi can be utilized for the broadcasting the data. When $\delta_{NIS}$is utilized as the network interface-selection interval the probability that a network interface selection is a success or failure can be evaluated in both cases by,

$$P_{NIS-Fail}(\delta_{NIS}) = \frac{\mu_{Wi-Fi}}{\lambda_{Wi-Fi} + \mu_{Wi-Fi}} + \frac{\lambda_{Wi-Fi}}{\lambda_{Wi-Fi} + \mu_{Wi-Fi}} \quad (9)$$

$$P_{NIS-Succ}(\delta_{NIS}) = \frac{\mu_{Wi-Fi}}{\lambda_{Wi-Fi} + \mu_{Wi-Fi}} - \frac{\lambda_{Wi-Fi}}{\lambda_{Wi-Fi} + \mu_{Wi-Fi}} \times e^{-(\lambda_{Wi-Fi}+\mu_{Wi-Fi})^{\delta_{NIS}}} = 1 - P_{NIS-Fail}(\delta_{NIS}) \quad (10)$$

Hence, the expected number of network interface-selection events is done$E[N_{NIS}]$can be computed by (11) by utilizing$P_{NIS-Succ}(\delta_{NIS})$. $E[T_{3G}]$is evaluated by (12) utilizing$E[N_{NIS}(\delta_{NIS})]$and δ_{NIS}:

$$E[N_{NIS}(\delta_{NIS})] = \frac{1}{P_{NIS-Succ}(\delta_{NIS})} \quad (11)$$

$$E[T_{3G}] = E[N_{NIS}(\delta_{NIS})] \times \delta_{NIS} \quad (12)$$

For$E[T_{Wi-Fi}]$, calculate easily using (13) given the memory-less property of an exponential distribution [26]–29]:

$$E[T_{Wi-Fi}] = \frac{1}{\mu_{Wi-Fi}} \quad (13)$$

TC_{NIS} selections while one network cycles. TC_{NIS}modifies based on the network interface-selection interval. When $\delta_{NIS}$is utilized as the interval, the total usage of energy of network interface selection while one network cycle, $TC_{NIS}(\delta_{NIS})$, can be evaluated by

$$TC_{NIS}(\delta_{NIS}) = e_{NIS} \times E[N_{NIS}(\delta_{NIS})] \quad (14)$$

Finally, it is required to compute and predict the energy usage of the mobile device with 3G and Wi-Fi interfaces while one network cycle utilizing entire equations above.

Delay modelling with 3G and Wi-Fi network interfaces

The transfer of data delay is also a significant problem to conceive, when computing the efficiency of a data transfer. Here, the model the delay of a mobile device is utilizing with 3G and Wi-Fi network interfaces. Evaluate and predict the expected delay based on the amount of the requested data transfer. Determine the delay as the amount of time necessary to transfer the requested data. Simply utilize three data transfer policies: the 3G-only, the Wi-Fi-only, and the 3G-and-Wi-Fi policies. The delay of every policy can be evaluated as follows. Avoid the queuing delay of the requested data transfer in our data transfer delay analysis.

1) Using 3G Only: When utilizing the 3G-only policy, utilize only 3G to transfer the requested data. Compute the wonted delay simply via (10). In (10), $\mathrm{E}[\mathrm{D}_{3\mathrm{G}}]$represents the expected delay of the 3G-only policy and $\mathrm{E}[\mathrm{R}_{3\mathrm{G}}]$represents the expected data transfer rate of 3G. BD, in units of MB, represents the amount of the requested data transfer or the backlogged data. The expected delay of 3G can only rise linearly based on BD and $\mathrm{E}[\mathrm{R}_{3\mathrm{G}}]$. Easily foresee that the expected delay reduced as $\mathrm{E}[\mathrm{R}_{3\mathrm{G}}]$increases:

$$E[D_{3G}] = \frac{BD}{E[R_{3G}]} \tag{15}$$

Using Wi-Fi Only: When utilizing the Wi-Fi-only policy, need to utilize only Wi-Fi to transfer the data. Increase the energy efficiency of data transfer, but the delay may be maximized due to the service area of Wi-Fi access points is restricted in few areas. Evaluate the expected delay when utilizing Wi-Fi only, $\mathrm{E}[\mathrm{D}_{\mathrm{Wi-Fi}}]$, by

$$\begin{aligned} E[D_{Wi-Fi}] = E[A_{Wi-Fi}] & \\ \times \Bigg((NS_{Wi-Fi}) \times E[T_{3G}] & \\ + \frac{BD}{E[R_{Wi-Fi}]} \Bigg) & \\ + (1 - E[A_{Wi-Fi}]) & \\ \times \Bigg((NS_{Wi-Fi}) \times E[T_{3G}] & \\ + \frac{BD}{E[R_{Wi-Fi}]} \Bigg) & \end{aligned} \tag{16}$$

Where $NS_{Wi-Fi} = \left[\frac{BD}{(E[R_{Wi-Fi}] \times E[T_{Wi-Fi}])}\right]$

In (11), $\mathrm{NS}_{\mathrm{Wi-Fi}}$represent the number of demanded minimum network cycles to broadcast the requested data when utilzing the Wi-Fi-only policy. When a data transfer request increases, the network connection may be either 3G or Wi-Fi. If the data transfer begins with a Wi-Fi connection, the network cycle has an order of Wi-Fi and 3G. Else, the network cycle has an order of 3G and Wi-Fi. So, we have to assume the accessibility of Wi-Fi. The accessibility of Wi-Fi $\mathrm{E}[\mathrm{A}_{\mathrm{Wi-Fi}}]$can be measure as $\left(\frac{\mathrm{E}[\mathrm{T}_{\mathrm{Wi-Fi}}]}{\mathrm{E}[\mathrm{T}_{3\mathrm{G}}]} + \mathrm{E}[\mathrm{T}_{\mathrm{Wi-Fi}}]\right)$, or $\alpha \times \mathrm{A}_{\mathrm{Wi-Fi}}[\mathrm{t}] + (1-\alpha) \times \mathrm{E}[\mathrm{A}_{\mathrm{Wi-Fi}}]$, where t is the network cycle index. Use $\mathrm{E}[\mathrm{A}_{\mathrm{Wi-Fi}}]$to represent the future availability of Wi-Fi.

Using Both 3G and Wi-Fi: When utilzing both 3G and Wi-Fi, we utilize both 3G and Wi-Fi interdependent to transfer the data. While we significantlyutilize 3G to transfer the data, via the periodic wireless network interface-selection events, Wi-Fi is also utilzied to transfer the data in order to minimize the amount of energy used and the delay. The delay can be minimized comparatively more when broadcasting the huge amounts of data. Evaluate the expected delay when utilizing 3G and Wi-Fi together, $E[D_{3G|Wi-Fi}]$, by

$$\begin{aligned} E[D_{3G|Wi-Fi}] = E[A_{Wi-Fi}] \Big((NS_{3G|Wi-Fi} & \\ - 1)(E[T_{3G}] + E[T_{Wi-Fi}]) + \beta_1 \Big) & \\ + (1 - E[A_{Wi-Fi}]) & \\ \times \Big((NS_{3G|Wi-Fi} - 1) & \\ \times (E[T_{3G}] + E[T_{Wi-Fi}]) + \beta_1 \Big) & \end{aligned} \tag{17}$$

where $NS_{3G|Wi-Fi} = \frac{BD}{(E[R_{3G}] \times E[T_{3G}]) + (E[R_{Wi-Fi}] \times E[T_{Wi-Fi}])}$

In (12), $NS_{3G|Wi-Fi}$represents the number of network cycles necessary to transfer the requested data when utilizing both 3G and Wi-Fi. Similar to the Wi-Fi-only policy, a data transfer request may increase in either 3G or Wi-Fi. So, we also have to assume the accessibility of Wi-Fi when computing the delay:

If $\left[\frac{RD}{E[R_{Wi-Fi}] \times E[T_{Wi-Fi}]}\right] \geq 1$
Then $\beta_1 = E[T_{Wi-Fi}] + \frac{(RD - (E[R_{Wi-Fi}] \times E[T_{Wi-Fi}]))}{E[R_{3G}]}$
Else $\beta_1 = \left[\frac{RD}{E[R_{Wi-Fi}]}\right]$
If $\left[\frac{RD}{E[R_{3G}] \times E[T_{3G}]}\right] \geq 1$ Then $\beta_2 = \frac{RD}{E[R_{3G}]}$

where $RD = BD - \left(NS_{3G|Wi-Fi} - 1\right) \times (E[R_{3G}] \times E[T_{3G}] + E[R_{Wi-Fi}] \times E[T_{Wi-Fi}])$

The amount of$E[R_{3G}] \times E[T_{3G}] + E[R_{Wi-Fi}] \times E[T_{Wi-Fi}]$ data can be broadcasted while one network cycle. At the time of the the last network cycle of data transfer, 3G or Wi-Fi or both 3G and Wi-Fi may be utilized to broadcast the residual data. It is required to compute the delay for the last network cycle independently. Here, $\beta_1$and $\beta_2$represent the expected delays for the last network cycle for the two cases.

Initially need to compute $\beta_1$and β_2, we have to evaluate the amount of residual data (RD) to be broadcasted while the last network cycle. If RD is higher than the amount of data which can be broadcasted by the first network which is utilized (3G or Wi-Fi) while the last network cycle, then utilize both 3G and Wi-Fi to broadcast the residual data while the last network cycle. Else, we can utilize only 3G or Wi-Fi to transfer the residual data.

Particle Swarm Optimization (PSO) is an algorithm Inspired from the nature social behavior and dynamic movements and communications of insects, birds and fish [28-29]. The main strength of PSO is its fast convergence, comparing with many global optimization algorithms like Genetic Algorithms (GA), Simulated Annealing (SA) and other global optimization algorithms. In proposed scheme, the energy consumption of Wi-Fi and 3G are calculated by using (16) and (17). The PSO is used to optimize the energy value in Wi-Fi and 3G. The key concept is dealing with changes in velocity. In this proposed method, the main idea of PSO is as follows. For the each input channel in d dimension, it could update its velocity and position using, (18) and, (19). Where r_1 and r_2 are two channels in the range [0, 1], V_{id} is the momentum, ω_{id} is the inertia weight, C_1 is the cognitive learning parameter and C_2 is the social collaboration parameter. $X_{id} = (x_{i1}, x_{i2}, \dots x_{id})$is the energy of the ith particle, $P_i = (p_{i1}, p_{i2}, \dots p_{id})$ represents the best previous position (i.e. the position with the highest fitness energy value).

$$V_{id} = \omega_{id} V_{id} + C_1 r_1 \left(p_{id} - X_{id}\right) + C_2 r_2 (p_{gd} - X_{id}) \quad (18)$$

$$X_{id} = X_{id} + V_{id} \quad (19)$$

Inertia Weight plays an important role in the process of providing balance between exploration and exploitation. It determines the contribution rate of a particles previous velocity to its velocity at the current time step. Different types of inertia weights were mentioned like Constant, Random, Adaptive inertia weight and many other types. A modified version of PSO was proposed, the main idea of this modified version is as in the following equations. For the ith particle in d dimension, it could update its velocity and energy using (20) and (21)

$$V_{id} = \lambda\left[\omega_{id} V_{id} + C_r r_1 (p_{id} - X_{id}) + C_2 r_2 (p_{gd} - X_{id})\right] \quad (20)$$

$$X_{id} = X_{id} + (\omega V_{id}) \quad (21)$$

Where λ is a convergence factor, which can be calculated using, (22)

$$\lambda = \frac{2}{\left|2 - C - \sqrt{C^2 - 4C}\right|} \quad (22)$$

Where $C = C_1 + C_2$, In the proposed Algorithm ω_{id} could be calculated using, (23) where t is iterate of overall iterations and T_{max} is the maximum number of iterations. With the increasing of t, parameter ω will be decreased linearly from 0.9 to 0.4

$$\omega_{id} = 0.9 - \frac{t}{T_{max}} * 0.5 \quad (23)$$

Simulation Results

Here, a simulation is done to compute AWNIS and AWNIS-PSO. Fig. 4 shows an example of the network environment utilized in the simulation. As shown in Fig. 4, the network field is classified into Wi-Fi service areas and 3G service areas. 3G wraps-up entire network field. The service areas of Wi-Fi were restricted. A user with a mobile device moves around inside the network field. The mobility of the user differs among 1 m/s and 10 m/s.

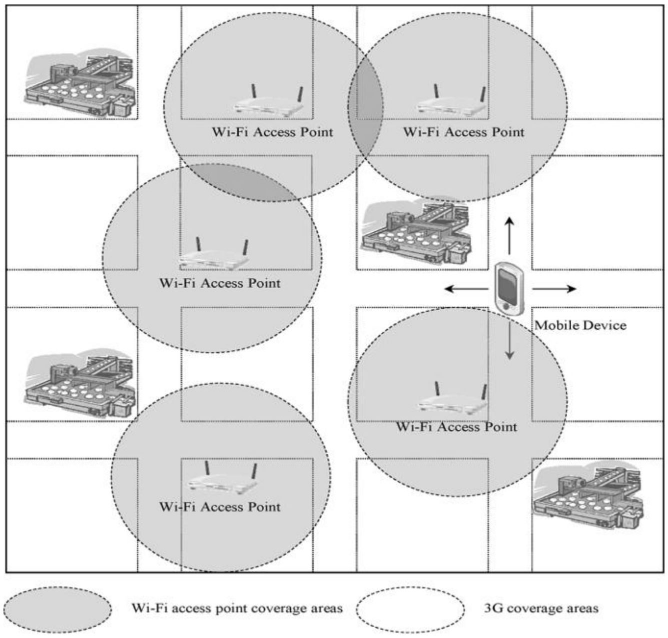

Figure 4: Example of the Network Environment used in the Simulation

Table 1 shows the simulation parameters used in the simulation. Simulation results performed each simulation 100 times to acquire the average energy utilization and the data transfer delay.

Table 1
Simulation Parameters

Parameters	Value
Network Field Size	1000 m x 1000 m
Workloads	10,50,100,150,200 KB/s, ECG, realistic traffic
Energy cost of 4G for data transferring	33.65 J/MB
Energy cost of 3G for data transferring	28.5 J/MB
Energy cost of Wi-Fi for data transferring	12.9 J/MB
Energy cost of a network selection interval	5.9 J
Initial network interface selection interval	30 s
Maximum network interface selection interval	300 s
Wi-Fi	802.11 g
3G	HSPA
The number of access points	10,15,20,25
The coverage of an access point	100 m radius
User mobility	1 m/s -10 m/s

Compute the performance of AWNIS and AWNIS-PSO as distinguished with the following five network interface-selection policies with respect to its energy consumption and data transfer delay. Additionally, we need to determine the two optimal policies which optimally utilize 3G, 4G-and-Wi-Fi and optimally utilization of Wi-Fi-only policies. Consider that the accurate status of Wi-Fi is known for these two optimal policies. These two optimal policies can modify the network interface to Wi-Fi at the perfect time then the Wi-Fi becomes accessible. So, periodic network interface selection isn't necessary in these two optimal policies and its cost isn't noted in the energy consumption, Wi-Fi can be used to the extreme but this consideration isn't realistic in the real world. So, the two optimal policies are considered to be energy efficient and have the shortest data transfer delay when distinguished with the rest of the policies. Assume the two optimal policies as the baseline; optimal using the 3G, 4G and-Wi-Fi policy and optimal using the Wi-Fi-only policy.

Using Wi-Fi only policy with AWNIS and AWNIS-PSO: This policy uses only Wi-Fi to transfer the data. Nevertheless, this policy does dynamic network interface selection by AWNIS and AWNIS-PSO. The network interface-selection interval modifies based on the network environment.

Using 3G, 4G and Wi-Fi policy with AWNIS and AWNIS-PSO: This policy utilizes both 3G and Wi-Fi when broadcasting the data and it does the dynamic network interface selection by AWNIS and AWNIS-PSO.

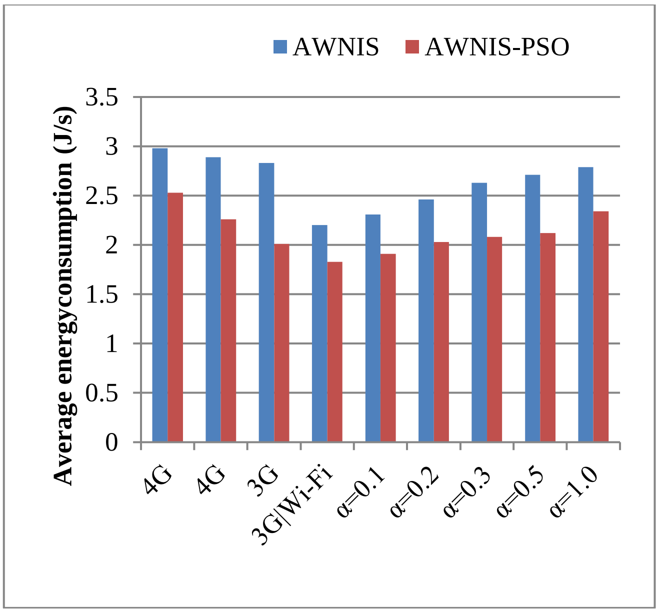

Figure 5: Average Energy Consumption Comparison (I) According to the Coefficient Value α, Where the Number of APs is 15

Figs. 5, the performance of AWNIS and AWNIS-PSO differs based on the coefficient value. If it is 0.1, AWNIS-PSO showed the best performance with respect to energy consumption. This shows that when computing the optimal network detection interval, it is more significant to assume the entire network environment rather than considering only the recent information. According to these observations, set the coefficient to 0.1 in the simulations.

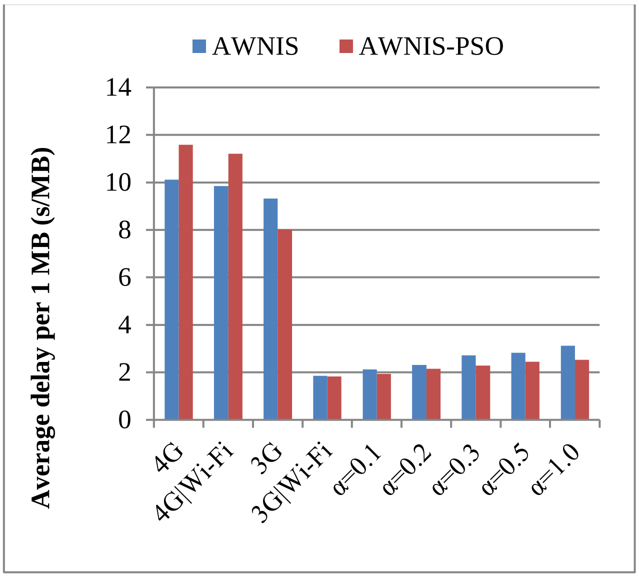

Figure 6: Average Data Transfer Delay Comparison (I) According to the Coefficient Value, where the number of APs is 15

Figs. 6, the performance of AWNIS and AWNIS-PSO differs based on the coefficient value α. If it is 0.1, AWNIS-PSO showed the best performance with respect to delay. This shows that, when evaluating the optimal network detection interval, it is more significant to assume the entire network environment rather than considering only the recent information.

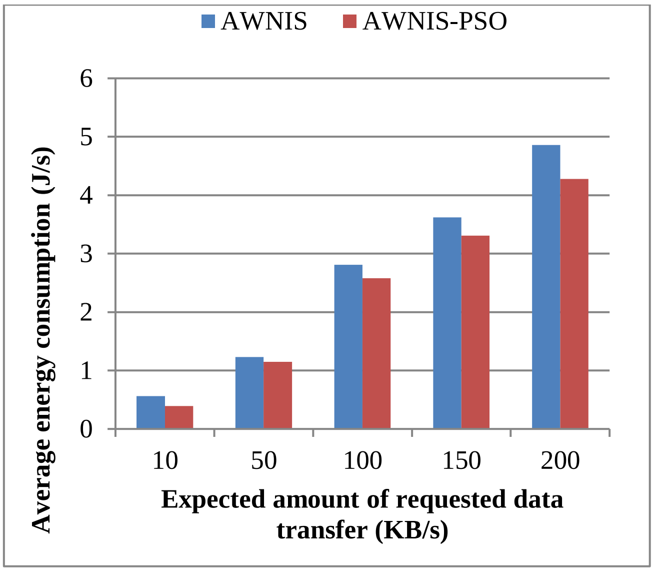

Figure 7: Average Energy Consumption Comparison According to the Expected Amount of Requested Data Transfer where the number of APs is 15 and for the Policies without AWNIS is 30 s

Fig. 7 shows the Average energy consumption based on the (expected amount of requested data transfer), where the number of APs is 15 and the static is 30 s for the policies without AWNIS. According to Fig. 7, the average amount of energy consumed will be increased. The 3G-only policy use the most energy when distinguished with the rest of the policies since the 3G-only policy only utilizes 3G as its network constantly and moreover 3G is less energy-efficient than Wi-Fi. The two optimal policies are the most energy-efficient policies. Overall, the policies with the proposed AWNIS-PSO show better performance than the others.

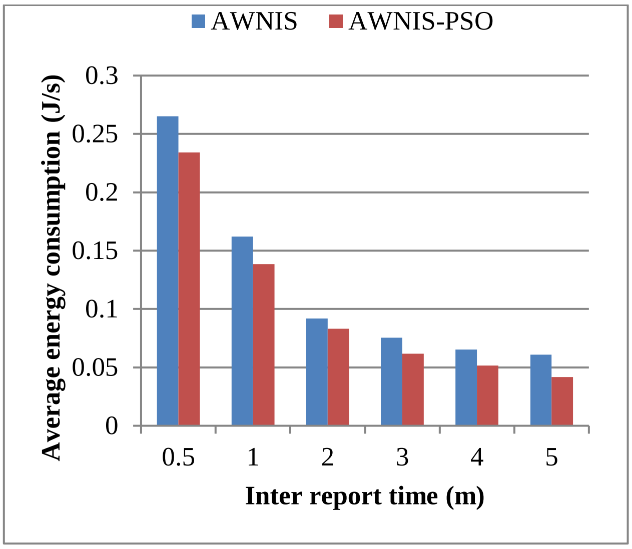

Fig. 8: Average energy consumption and delay comparison (I) between AWNIS and AWNIS-PSO with the ECG Workload, where the number of APs is 15. (a) Average energy consumption according to the inter-report time

The ECG workload is a real workload that broadcasts 270 KB of sensed data to a monitoring server at every report time. This workload is common to regularly report the machine state in an industrial environment. Fig. 8 shows that the average usage of energy and delay among AWNIS and Context-For-Wireless with the ECG workload. As shown in Fig. 16, proposed AWNIS-PSO used less energy than AWNIS when the inter-report time has a comparatively high value. Alternatively, when the inter-report time has a comparatively low value, AWNIS-PSO used less energy than AWNIS, it considers more network interface selection events, on average, as the inter-report time becomes short. In short, if the inter-report time is comparatively short, AWNIS-PSO method is more effective than AWNIS

Conclusion and Future Work

In this paper, presented as new energy efficient and route selection schemas for industrial mobile device that is equipped with 3G and Wi-Fi network interfaces. According to the Hidden Markov Model (HMM) mathematical modeling, examined the energy consumption and delay of the mobile device when utilizing 3G and Wi-Fi to transfer data. According to the examined results, an Adaptive Wireless Network Interface-Selection scheme (AWNIS) with Particle Swarm Optimization (AWNIS-PSO) is specifically designed for industrial mobile devices. Proposed AWNIS-PSO utilizes a dynamic network interface-selection interval to link the energy-efficient Wi-Fi. AWNIS-PSO scheme is well fit for industrial wireless networks since it is dynamically adapted to the network-selection interval in order to minimize the usage of energy, based on the network environment. Additionally, AWNIS-PSO scheme can be linked with other network interface-selection policies. The simulation output shows that the proposed scheme efficiently minimizes the amount of used energy, while assuring a specific level of data transfer delay. AWNIS-PSO can assure a specific level of data transfer delay performance while reducing the amount of used energy, future work concentrates on reducing the time consumption to finish the process of AWNIS-PSO

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