Journal of Engineering and Applied Sciences 12 (Special Issue 5): 7063-7068, 2017
ISSN: 1816-949X

An Efficient Modified Binary Particle Swarm Based on Task Allocation

Bilal Mishaal Mohammed and Ravie Chandren Muiyandi
Faculty of Technology and Information Science,
Center for Software Technology and Management (SOFTAM), University Kebangsaan,
Bangi Selangor, Malaysia

Abstract: Wireless Sensor Networks (WSN) have gained widespread popularity in recent years in the industry because of the many unique advantages they offer over conventional networks such as robustness, ability to cover wide and hard-to-reach areas, mobility of nodes and dynamic network topology among others. One of the most important areas of the application of WSNs is the execution of complex computational tasks. Due to the energy and resource constraints of a single node in the WSN these tasks often require collaborative in-network processing among multiple heterogeneous nodes. Owing to the absence of a fixed infrastructure, WSNs are forced to operate solely on limited amounts of battery capacity and processing power which limits their computational performance. Due to this limitation, development of task allocation optimization algorithms for WSNs is of paramount importance. Previously a Modified Binary Particle Swarm Optimization (MBPSO) algorithm had been proposed to optimize the process of allocating tasks to the nodes of a WSN. However, the approach has ignored an important constraint for the feasibility of the solutions when the nodes are heterogeneous. Moreover, the handling of the connectivity constraint has led to aggressive transition in the searching space which as a result creates a risk of missing the best solution or getting stuck in local minima in order to resolve these two issues a new constraint which dictates that the total energy required by the tasks from a node should be more than the initial energy of the node has been included in this approach has been added. Also, for meeting the connectivity constraint, instead of all the neighbor nodes of an already participating node, only one random node has been added. The simulation results of this approach on a WSN was performed which visibly improved the speed of convergence and prevented the algorithm from reaching a local-minima an improvement percentage of 8% in the fitness value. Moreover, the proposed approach was proven to always provide feasible solutions which satisfied the energy consideration of the nodes.

Key words: Wireless sensor networks, task allocation optimization algorithm, binary particle swarm optimization, heterogeneous, neighbor nodes, connectivity

INTRODUCTION

In-network processing has become an indispensable tool in recent years for applications which require computationally intense in-network processing tasks to be executed in a sequential manner such as tracking (Fu *et al*., 2012) distributed visual surveillance (Han *et al*., 2012) and target localization (Karakaya and Qi, 2011). In-network processing in Wireless Sensor Networks (WSN) possesses the primary advantage of being more energy-efficient than sending all the raw data to the sink node (Fasolo *et al*., 2007). Moreover, it can also reduce the communication volume and improve the real-time performance of the WSN (Tian and Ekici, 2007).

A WSN is a network of communicating nodes (Bal *et al*., 2009); each incorporated with sensors which collect, process and transmit real-time data to the sink node. Sensor nodes contain portable energy sources and are battery powered which significantly limits and constrains their energy supply. Most in network processing tasks require considerable processing power which may be beyond the capability of a single node. Coupled with the limited and portable energy sources of the sensor nodes as mentioned above, this makes the optimization of energy consumption in a WSN of paramount importance.

The sensor nodes are not only able to function as independent processing units but are also able to connect and collaborate with other nodes in the WSN through direct or multi-hop communication links. This connectivity enables the WSN to function as a parallel computing system through data exchange among the sensor

Corresponding Author: Bilal Mishaal Mohammed, Faculty of Technology and Information Science,
Center for Software Technology and Management (SOFTAM), University Kebangsaan, Bangi Selangor, Malaysia

nodes. This connectivity thus enables the WSN as a whole to execute computationally intense tasks which are much beyond the capacity of a single node. This can be achieved by decomposing the tasks into smaller subtasks which are then executed concurrently on the sensor nodes. To harness the capabilities of the parallel computing system as being able to execute computationally intense tasks it is necessary to construct mechanisms which allocate each task to the most suitable group nodes while satisfying the application requirements. This process of allocating tasks to a group of nodes in the most optimal and cost-effective manner is known as task allocation optimization.

In addition to energy conservation and balanced energy consumption to prolong the network lifetime being the primary goals of task allocation optimization, many applications such as distributed visual surveillance and tracking also require that the tasks be finished in the shortest possible amount of time. Therefore, the tasks execution time should also be considered in the task allocation optimization as a metric which needs to be minimized. Since, minimizing task execution time is often at odds with trying to balance energy consumption across the WSN, trade-offs among multiple variables which are often at conflict with each other becomes the primary objective of task allocation optimization algorithms.

Literature review: Various algorithms have been designed to solve and optimize the problem of task allocation in networks. As collaborative networking using heterogeneous nodes keeps gaining popularity as an indispensable tool for performing complex and large-scale tasks, this issue will continue to be of significant interest for research and development in the foreseeable future.

Heuristic searching approach: By Yang *et al*. (2013), a Modified Binary Particle Swarm Optimization (MBPSO) algorithm has been proposed to optimize the process of allocating tasks to the nodes of a WSN. However, this algorithm results in the addition of an excessive number of nodes to the WSN which results in an increase in the energy consumption of the network. Moreover, this algorithm often results in obtaining the local minima and not the absolute minima of the objective function.

Furthermore, the formulation of the objective function ignores the initial energy of the nodes. This could result in not satisfying the task workload and connectivity constraint despite reaching the optimal solution.

Xiao *et al*. (2009) propose a novel prediction model based on MinMin heuristic (P-MinMin) search algorithm. Simulation results have showed that the proposed algorithm outperforms existing task allocation algorithms in terms of energy consumption and capability of meeting real-time requirements demanded by WSN applications. The proposed algorithm is germane only for direct communication links between nodes and fails to account for multi-hop communication links.

Neural networks approach: By Haihao *et al*. (2007), a novel method of task allocation for a collaborative technique in a WSN has been proposed based on elastic neural networks with the aim of reducing the energy consumption of the network. A minimum energy constraint of a node is incorporated in this approach to build fully connected subgraphs of neurons to allocate tasks to a WSN in the most optimal manner possible in the event dynamic coalition tasks compete for the resources of the same node. Simulation results have proved that this approach is able to significantly reduce the energy consumption of the WSN compared to conventional approaches. Results of this algorithm being implemented on actual network systems would be required to validate its effectiveness.

Price formulating scheme: An adaptive task allocation scheme that accounts for the unique characteristics of the WSN environment such as unexpected communication delay and node failure is proposed by Edalat *et al*. (2009). The proposed architecture of this scheme models the nodes as sellers who intimate the deployment price for a task to the consumer. The unique advantage of this approach lies in the fact that a price formulating scheme is incorporated into it as it is able to continuously adapt to changes in resource availability. Moreover, this scheme also accommodates for the undesirable event of node failure while the WSN is in operation. Simulation results have shown that this scheme acclimatizes itself to unexpected environmental changes and uncertain network conditions much more effectively and dynamically than conventional scheduling schemes while performing better in energy utilization and distribution. A similar scheme has also been proposed by Edalat *et al*. (2011) where the heterogeneous sensor nodes are modeled as bidders who bid the cost value in terms of available resources for performing the most suitable subset of the application's tasks.

Cluster based approach: By ElGammal and Eltoweissy, (2011), the task allocation problem is visualized as a clustering problem which employs an affinity propagation inspired clustering protocol to assign tasks to nodes achieving near-optimal solutions at only a fraction of the optimal solution cost. Sharma *et al*. (2013) present a sensor lifetime enhancement technique with the goal of balanced power distribution which accommodates cases of heterogeneous power capacities of the different nodes of the WSN. The dynamics of task reallocation including its toll on network resources and effect on system stability will have to be covered in future works to make this algorithm more feasible and robust.

Hybrid approaches: By Huang *et al*. (2011), the Integer Linear Programming Formulation (ILP) is extended to account for processing and communication energy. A Simulated Annealing with Timing Adjustment (SA-TA) heuristic is also proposed to accelerate the optimization process. While the proposed ILP formulation can achieve results very close to the global optimum it suffers from longer execution time. Another drawback of this model is that it proposes a very simplified energy model. To incorporate a more precise energy model, the leakage power should be considered and the power management features of the processor should be taken into account.

Voinescu *et al*. (2010) considers a task scheduling algorithm for the sub-tasks of an application network in circumstances where the WSN task-based systems are required to provide energy to entities outside the network while optimizing energy usage and network lifetime. This algorithm only works for a mesh topology network and future work would have to account for multi-hop connections between the nodes.

Yang *et al*. (2013) employs a soft real-time Fault-tolerant Task Allocation Algorithm (FTAOA) by using a Primary/Backup (P/B) technique to support a fault tolerance mechanism for a WSN. Resource utilization is improved by allocating tasks to the nodes with high performance in terms of load, energy consumption and failure ratio. The feasibility and effectiveness of this method has been demonstrated by simulation results which proved its capability to reach a satisfactory optimal solution within a short period of time. In addition to the lack of experimental results of this algorithm being implemented on an actual network to validate it further, the algorithm also suffers from unnecessary redundancy which could be addressed in future works.

Problem statement: Previously, a Modified Binary Particle Swarm Optimization (MBPSO) algorithm (Yang *et al*., 2013) had been proposed to optimize the process of allocating tasks to the nodes of a WSN. MPBSO is a binary variant of the famous PSO optimization algorithm that has been proposed by Kennedy and Eberhart. This approach is efficient in resolving the optimization of the task allocation. MBPSO is a modification of original PSO to work on binary representation of particles with more efficient activation functions it is done by Yang *et al*. (2013) and tested on task allocation. However, Yang *et al*. (2013) have ignored an important constraint regarding the energy which has led to non-feasible solutions. In addition, the researchers have tried to maintain the connectivity constraint while generating new solutions which is important for feasibility. But their approach has led to aggressive transition in the searching space from one region to another which creates a risk of local minima. It is meant by local minima the solution that is only good in its local region while it is not the best overall.

MATERIALS AND METHODS

This study, provides solution for each of the two mentioned problems. Resolving the task allocation for heterogenous energy nodes to rectify the issue of the objective function ignoring the initial energy of the nodes, some modifications to the approach employed in the MBPSO algorithm are introduced. The fitness function of the MBPSO algorithm can be expressed as:

$$f(X) = W_1 \bullet T_n(X) + W_2 \bullet E_n(X) + (1-W_1-W_2) \bullet D_n(X) \tag{1}$$

$$\begin{cases} T_n(X) = T_n(X)/T_{max} \\ E_n(X) = E(X)/E_{max} \\ D_n(X) = D(X)/D_{max} \end{cases} \tag{2}$$

The $T_n(X)$, $E_n(X)$ and $D_n(X)$ terms in Eq. 1 are scaled to the range 0-1 . Since, the sum of the weights (W_1 and W_2) is 1, the value of f (X) is always in the range 0, 1. Each particle in the MBPSO algorithm is represented as an m X n matrix where m is the number of tasks and n is the number of nodes as illustrated in Fig. 1.

To resolve the issue of the objective function ignoring the initial energy of the nodes a constraint that states that the sum of the required energy by the tasks from a node must be bigger than the initial energy of the node and which should be satisfied for all the system nodes is added to this approach. This constraint is expressed in Eq. 3 for every node I:

$$\sum_{j=1}^{\text{Number of tasks}} E_{i,j} > E_0 \tag{3}$$

where, $E_{i,j}$ denotes the required energy of node i to execute task j. In the event the constraint is not satisfied, the particle is rejected and the fitness value is set to 1 which corresponds to the worst case scenario.

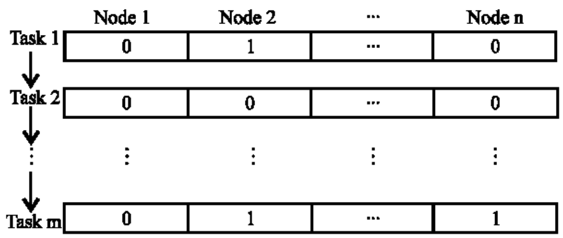

Fig. 1: Illustration of a particle in the MBPSO approach

RESULTS AND DISCUSSION

In order to validate the proposed approach, the modified algorithm is implemented on a WSN simulated in MATLAB environment. The network consists of 30 nodes which are required to execute 27 tasks. The processing speed of the nodes is uniformly distributed in the range 3, 10 MCPS, the power of the nodes is uniformly distributed in the range 10, 100 mW and the initial energy of the nodes is distributed in the range 100-500 mJ. The maximum computation capacity of a node is 500 KCC and its maximum communication load is 400 bytes at any given time.

The communication load of the tasks is uniformly distributed in the range 7000-10000 bytes and the computation load is uniformly distributed in the range 6000-10000 KCC.

The performance of the proposed approach is compared with the original approach. The performance of the proposed approach in regards to solving the issue of adding an unnecessarily high number of nodes by comparing it against the original approach is illustrated in Fig. 2.

As illustrated in Fig. 3a and b, it is clear that proposed approach improves the speed of convergence and was able to avoid being stuck in a local minima like the benchmark. After examination, it was found that the newly proposed constraint was satisfied by the two resultant particles. Figure 4 illustrates the initial energy and the required energy of the nodes in the proposed and the original approaches. It is clear that all the nodes have initial energy greater than the required energy.

Another simulation was performed after modifying the initial energy of the nodes to be uniformly distributed in the range 75, 200 mJ which is illustrated in Fig. 5.

As illustrated in Fig. 5, it is evident that benchmark converged to a valid particle whereas the proposed approach did not. However, it was found that the particle did not satisfy the newly introduced constraint in the cases of node 3 and 15.

It is thus evident that being able to acquire a particle which satisfies the original constraints in the benchmark

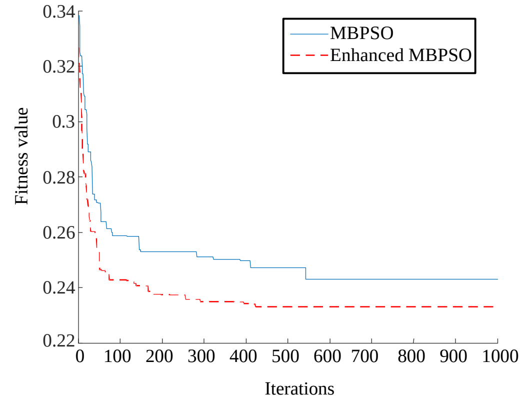

Fig. 2: Fitness value with respect to iterations

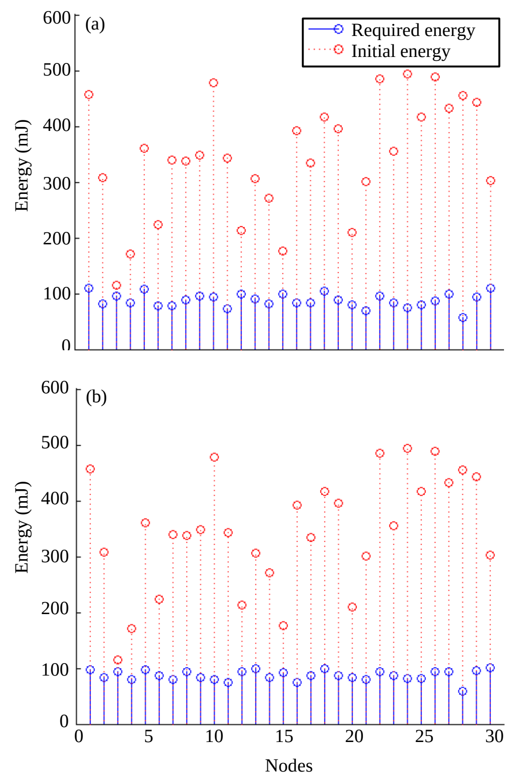

Fig. 3: a, b) Energy with respect to nodes in the proposed approach; energy with respect to nodes

does not guarantee that the particle would be able to satisfy the newly introduced constraint. Simulation experiments, were performed after updating the initial energy of the nodes to be uniformly distributed in the range 75-250 mJ. The results of this simulation is showed in Fig. 6a and b.

It is evident from Fig. 6 that both the approaches reached a particle that satisfied their corresponding constraints. However, it was found that the valid particle reached by the proposed approach satisfied the newly

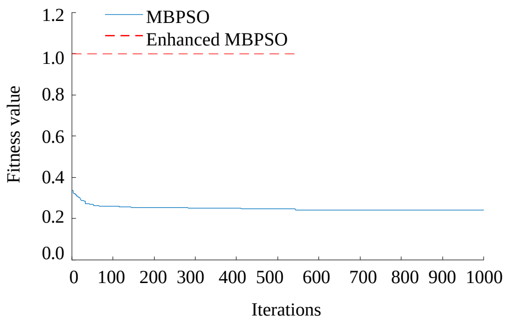

Fig. 4: Fitness value with respect to iterations for the proposed approach and the benchmark rang (75, 200 mJ)

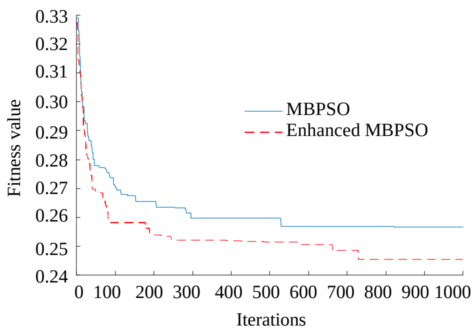

Fig. 5: Fitness value with respect to iterations for both benchmark and proposed approach (75, 250 mJ)

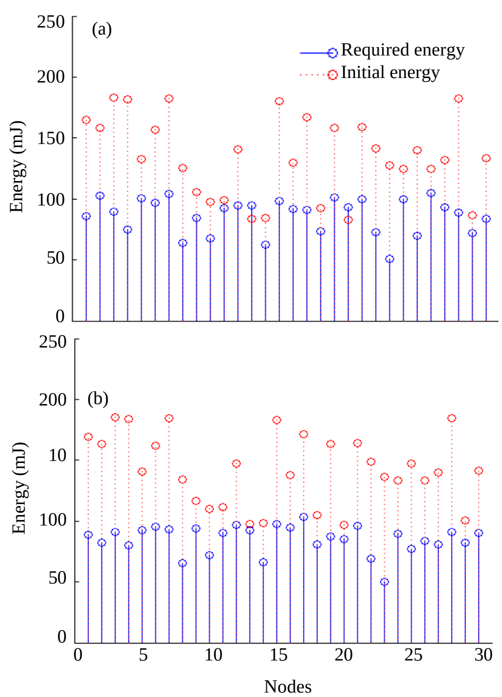

Fig. 6: a, b) Energy of nodes when it is uniformly distributed in the range 75, 250 m; energy with respect to nodes in the proposed

introduced constraint while the valid particle reached by the original approach. Node 13 and 20 of theparticle reached by the initial approach was found to have initial energy less than the required energy. Figure 6a and b illustrates the initial energy and the required energy of the valid particle in both the approaches.

CONCLUSION

In this study, a Modified Binary Particle Swarm Optimization (MBPSO) algorithm had been improved. This work uses the MBPSO presented by Yang *et al*. (2013) and therefore, builds upon it an improvement scheme to resolve some drawbacks. We saw that the original work suffers from two drawbacks: first one is ignoring the case of heterogeneous nodes in energy which leads to non-feasible solution. The second one is the aggressive searching when the connectivity constraint is not met This leads to local minima while searching due to possibility of skipping absolute minima regions. To overcome these drawbacks, the binary particle swarm optimization based approach has been further modified in this work. Instead of adding all the neighbors of a node, only one neighbor is added in random to satisfy the task and connectivity constraints. Furthermore, a new constraint which requires the total energy needed by the tasks from a node to be more than the initial energy of the node has also been added in this approach. Simulation results of this approach on a WSN was performed in MATLAB environment and it visibly improved the speed of convergence and prevented the algorithm from reaching a local minimum. Moreover, the proposed approach was also proven to always provide a feasible solution which accounted for the initial energy of the nodes.

SUGGESTIONS

In the future research, validation of the approach could be carried out to test the proposed MBPSO algorithm in real time mode and to customize it to specific real world applications in various areas. Also, to adapt some routing protocol to perform task allocation in an online mode. Another future work is to further develop the model on more detailed network model and task models.

REFERENCES

Bal, M., W. Shen and H. Ghenniwa, 2009. Collaborative signal and information processing in wireless sensor networks: A review. Proceedings of the 2009 IEEE International Conference on Systems, Man and Cybernetics, October 11-14, 2009, IEEE, San Antonio, Texas, USA., ISBN: 978-1-4244-2793-2, pp: 3151-3156.

Edalat, N., W. Xiao, C.K. Tham, E. Keikha and L.L. Ong, 2009. A price-based adaptive task allocation for wireless sensor network. Proceedings of the 6th International Conference on Mobile Adhoc and Sensor Systems (MASS'09), October 12-15, 2009, IEEE, Macau, China, ISBN:978-1-4244-5114-2, pp: 888-893.

Edalat, N., W. Xiao, N. Roy, S.K. Das and M. Motani, 2011. Combinatorial auction-based task allocation in multi-application wireless sensor networks. Proceedings of the 9th International Conference on Embedded and Ubiquitous Computing (EUC'11), October 24-25, 2011, IEEE, Melbourne, Victoria, Australia, ISBN:978-1-4577-1822-9, pp: 174-181.

ElGammal, M. and M. Eltoweissy, 2011. Distributed dynamic context-aware task-based configuration of wireless sensor networks. Proceedings of the Conference on Wireless Communications and Networking (WCNC'11), March 28-31, 2011, IEEE, Cancun, Quintana Roo, Mexico, ISBN:978-1-61284-255-4, pp: 1191-1196.

Fasolo, E., M. Rossi, J. Widmer and M. Zorzi, 2007. In-network aggregation techniques for wireless sensor networks: A survey. Wireless Commun. IEEE., 14: 70-87.

Fu, Y., Q. Ling and Z. Tian, 2012. Distributed sensor allocation for multi-target tracking in wireless sensor networks. IEEE. Trans. Aerosp. Electron. Syst., 48: 3538-3553.

Haihao, L., L. Mei, S. Yi and Q. Deli, 2007. Research on task allocation technique for multi-target tracking in wireless sensor network. Proceedings of the International Conference on Mechatronics and Automation (ICMA'07), August 5-8, 2007, IEEE, Harbin, China, ISBN: 978-1-4244-0827-6, pp: 360-365.

Han, C., L. Sun, F. Xiao, J. Guo and R. Wang, 2012. A camera nodes correlation model based on 3D sensing in wireless multimedia sensor networks. Intl. J. Distrib. Sens. Netw., 8: 154602-1-154602-9.

Huang, J., C. Buckl, A. Raabe and A. Knoll, 2011. Energy-aware task allocation for network-on-chip based heterogeneous multiprocessor systems. Proceedings of the 2011 19th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP'11), February 9-11, 2011, IEEE, Ayia Napa, Cyprus, ISBN:978-1-4244-9682-2, pp: 447-454.

Karakaya, M. and H. Qi, 2011. Distributed target localization using a progressive certainty map in visual sensor networks. Ad Hoc Netw., 9: 576-590.

Sharma, S., M. Wazid, N. Gupta, D.P. Singh and R.H. Goudar, 2013. Data recovery with energy efficient task allocation in Wireless Sensor Networks. Proceedings of the 2013 International Conference on Emerging Trends in Computing, Communication and Nanotechnology (ICE-CCN'13), March 25-16, 2013, IEEE, Tirunelveli, India, ISBN:978-1-4673-5037-2, pp: 298-303.

Tian, Y. and E. Ekici, 2007. Cross-layer collaborative in-network processing in multihop wireless sensor networks. IEEE. Trans. Mobile Comput., 6: 576-590.

Voinescu, A., D.S. Tudose and N. Tapus, 2010. Task scheduling in wireless sensor networks. Proceedings of the 2010 6th International Conference on Networking and Services (ICNS'10), March 7-13, 2010, IEEE, Cancun, Mexico, ISBN:978-1-4244-5927-8, pp: 12-17.

Xiao, W., S.M. Low, C.K. Tham and S. Das, 2009. Prediction based energy-efficient task allocation for delay-constrained wireless sensor networks. Proceedings of the 6th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks Workshops (SECON Workshops'09), June 22-26, 2009, IEEE, Rome, Italy, ISBN:978-1-4244-3938-6, pp: 1-3.

Yang, J., H. Zhang, Y. Ling, C. Pan and W. Sun, 2013. Task allocation for wireless sensor network using modified binary particle swarm optimization. IEEE. Sens. J., 14: 882-892.