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A Study on Particle Swarm Optimization in Wireless-Sensor Networks

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Abstract—*Wireless-sensor networks (WSNs) are networks of au- tonomousnodesusedformonitoringanenvironment.DevelopersofWSNs face challenges that arise from communication link failures, memory and computational constraints, and limited energy. Many issues in WSNs are formulated as multidimensional optimization problems, and approached through bioinspired techniques. Particle swarm optimization (PSO) is a simple, effective, and computationally efficient optimization algorithm. IthasbeenappliedtoaddressWSNissuessuchasoptimaldeployment,nodelocalization,clustering,anddataaggregation .ThispaperoutlinesissuesinWSNs,introducesPSO,anddiscussesitssuitabilityforWSNapplications.Italsopresentsabr iefsurveyofhowPSOistailoredtoaddresstheseissues.*

Index Terms—*Clustering, data aggregation, localization, optimal de- ployment, particle swarm optimization (PSO), Wireless-sensor networks (WSNs).*

I. Introduction

WIRELESSSENSORnetworks(WSNs)areanemergingtechnology[1]thathaspotentialapplicationsinsurveillance,environmentandhabitatmonitoring,structuralmonitoring,healthcare,anddisastermanagement[2].AWSNmonitorsanenvironmentbysensingitsphysicalproperties.Itisanetworkoftiny,inexpensiveautonomousnodesthatcanacquire,process,andtransmitsensorydataoverwirelessmedium.Oneormorepowerfulbasestationsserveasthefinaldestina- tionofthedata.ThepropertiesofWSNsthatposetechnicalchallengesincludedenseadhocdeployment,dynamictopology,spatialdistribu-tion, and constrains in bandwidth, memory, computationalresources,and energy.

WSN issues such as node deployment, localization, energy-aware clustering, and data aggregation are often formulated as optimization problems.Traditionalanalyticaloptimizationtechniquesrequireenor- mouscomputational efforts, whichgrowexponentiallyastheproblem size increases. An optimization method that requires moderate mem- ory and computational resources and yet produces good results is de- sirable, especially for implementation on an individual sensor node. Bioinspired optimization methods are computationally efficient alter- natives to analytical methods. Particle swarm optimization (PSO) is a popular multidimensional optimization technique [3]. Ease of im- plementation, high quality of solutions, computational efficiency, and speed of convergence are strengths of the PSO. Literature is replete with applications of PSO in WSNs. The objective of this paper is to giveaflavorofPSOtoresearchersinWSNandtogiveaqualitativetreatment of optimization problems in WSNs to PSO researchers in order to promote PSO in WSN applications.

The rest of this paper is organized as follows: PSO and its rel- ative advantages are briefly outlined in Section II. SectionsIIIVIdiscussapplicationsofPSOinoptimaldeployment,localization,clustering,anddataaggregation(alsoreferredtoasdatafusion).Ineachof these sections, a specific WSN issue is introduced and a briefdescrip- tionofhowPSOisappliedtoaddresstheparticularissueispresented.

Finally,aprojectionoffuturePSOapplicationsinWSNsandconclud- ing remarks are given in SectionVII.

PSO: A BRIEFOVERVIEW

A. PSOAlgorithm

PSOmodelssocialbehaviorofaflockofbirds[3].Itconsistsofaswarmofscandidatesolutionscalledparticles,which exploreanndimensionalhyperspaceinsearchoftheglobalsolution(nrepresentsthenumberofoptimalparameterstobedetermined).Aparticlei occupiespositionX$_{id}$andvelocityV$_{id}$inthedthdimensionofthehy- perspace, 1 i s and1dn.Eachparticleisevaluatedthroughanobjectivefunction$f(x_1,x_2,\ldots,x_n)$,where$f$:R^nR.Thecost(fitness)ofa particleclosetotheglobalsolutionislower(higher)than thatofaparticlethatisfarther.PSOthrivestominimize(maximize)thecost(fitness)function.Intheglobal- bestversionofPSO,theposition → wheretheparticleihasitslowestcostisstoredas(pbest$_{id}$).Besides,gbest$_d$,thepositionofthebestparticle.Ineachiterationk,velocityVandpositionXareupdatedusing(1)and(2).Theupdateprocessisiterativelyrepeateduntileitheran acceptablegbestisachievedora fixed number of iterations k_{max}isreached.

$V_{id}(k + 1) = wV_{id}(k)+ \phi_1 r_1 (k)(pbest_{id}- X_{id})$
$+ \phi_2 r_2(k)(gbest_d - X_{id})$ (1)
$X_{id}(k + 1) = X_{id}(k)+ V_{id}(k +1)$ (2)
where $\phi_1$and $\phi_2$are constants, and $r_1(k)$ and $r_2(k)$ are random numbers uniformly distributed in [0, 1]. This is the basic "textbook" informationaboutPSO.PopularthemesofPSOresearchare:choiceof parameters and their ranges, iterative adaption of parameters, particle interactiontopologies,convergenceacceleration,adaptiontodiscrete, binary and integer domains, and hybridization with other algorithms. The state of the art in PSO is presented in[4].

B. Other OptimizationAlgorithms
Traditional-optimization methods include linear, nonlinear, and quadratic programming, Newton-based techniques, and interior-point methods. Their computational complexities grow exponentially with the problem size. Resource requirements and cost of mathematical programming engines (such as IBM ILOG CPLEX) used for linear, nonlinear, and quadratic programming make them unattractive for re- sourceconstrainednodes.Thisisthemotivationforheuristicalgorithms such as PSO, genetic algorithm (GA), differential evolution (DE),and bacterial foraging algorithm (BFA). GA facilitates evolution of the populationgenerationbygenerationusingoperatorssuchascrossover, mutation,andselection[5].DEissimilartoGA,butitusesadifferen- tial operator [6], which creates a new solution vector by mutating an existing one by a difference of randomly chosen vectors. BFAmodels theforagingbehaviorofbacteriathatusesacombinationofstraight

TABLE I
SUMMARY OF APPLICATIONS OF PSO IN WSN DEPLOYMENT

	Task of PSO	Optimization criterion	Algorithm	Ref.	Centralized/ Distributed	Study
Deployment	Position stationary nodes	Max. coverage	PSO-Voronoi*	[13]	Centralized	Simulation
	Position stationary nodes	Min. cost of sensor equipment	PSO-Traffic*	[14]	Centralized	Real Deployment
	Position mobile nodes	Max. coverage	PSGO	[15]	Centralized	Simulation
	Position mobile nodes	Max. coverage	VFCPSO	[16]	Combination of both	Simulation
	Position base stations	Max. energy efficiency	PSO Multi-Base*	[17]	Centralized	Simulation
Localization	Localize nodes	Min. localization error	PSO-Loc*	[21]	Centralized	Simulation
	Localize nodes	Min. localization error	PSO-Iterative	[11]	Distributed	Simulation
	Localize nodes	Min. localization error	PSO-Beaconless*	[22]	Distributed	Simulation
	Localize nodes	Min. localization error	PSO-Beaconless*	[23]	Distributed	Real Deployment
	Localize nodes	Min. localization error	PSO-4 Beacon*	[24]	Distributed	Simulation
EAC	Elect cluster-heads	Min. intra-cluster distance	PSO-Clustering*	[26]	Centralized	Simulation
	Elect cluster-heads	Max. network longevity	PSO-C*	[27]	Centralized	Simulation
	Elect cluster-heads	Max. network longevity	MSTree-PSO*	[29]	Centralized	Simulation
Data-fusion	Allocate optimal transmission power	Min. energy expenditure and error probability	PSO-Opt-Alloc*	[31]	Centralized	Simulation
	Determine local thresholds	Min. decision error	ABC-PSO	[32]	Centralized	Simulation
	Determine sensor configuration	Min. decision error and transaction time	BMPSO	[33]	Distributed	Simulation

* Authors refer to this algorithm by this name

line and random movements to reach nutrient-rich locations [7]. Ad- vantages of PSO over these alternatives are the following.
1) Ease of implementation on hardware orsoftware.
2) Availability of guidelines for choosing itsparameters.
3) High-qualitysolutionsbecauseofitsabilitytoescapefromlocal optima [8],[9].
4) Availabilityofvariantsforreal,integer,andbinarydomains[4].
5) Quick convergence [10],[11].

PSO with s number of n-dimensional particles that runs for k_{max}iterations requires k_{max}s fitness evaluations and memory for s n variables each for positions, velocities, and pbest, plus n variables for gbest. This can be prohibitively expensive on some nodes.

I. OPTIMAL WSNDEPLOYMENT
WSNdeploymentproblemreferstodeterminingpositionsforsensornodes(orbasestations)suchthatthedesired

coverage,connectivity,and energy efficiency can be achieved with as few nodes as possible [12]. Eventsinanareadevoidofanadequatenumberofsenornodesremain unnoticed; and the areas having dense sensor populations suffer from congestions and delays. Optimally deployed WSN assures adequate qualityofservice,longnetworklife,andfinancialeconomy.Available PSO solutions to the deployment problem are computed centrally on a base station for determining positions of sensors, mobile nodes, or base stations as summarized in TableI.

A. Stationary NodePositioning

Objective of the centralized, off-line PSO-Voronoi algorithm pro- posed by Aziz et al. in [13] is to minimize the area of coverage holes. The strategy is based on the principle that if each point in the region of interest (ROI) is covered by a sensor, then the whole ROI is cov- ered. Assessment of coverage involves sampling the ROI throughgrid scan. PSO–Voronoi circumvents this by Voronoi polygons around the sensors. PSO particles are the sensors' positions. For each particle, a set of Voronoi polygons are determined, and the vertexes of the poly- gons are treated as sample points. The cost function is the number of vertexesthatareuncoveredbysensors.PSOVoronoiachievesclosetoidealcoveragebutignoresthetimecomplexityofdeterminingVoronoi polygons.

Hu et al. have proposed PSO-Traffic for topological planning for a real world traffic surveillance application [14]. The study uses a large number of camera-loaded nodes, some of which require larger transmissionradiifacilitatedbyexpensivehigh-powertransmitters.The objective is to determine the nodes with high-power transmitters such thatthehighestpossibleconnectivityisachievedatthelowestpossible hardware expense. PSO-Traffic is binary PSO in which the particles representsequencesofsensors. PSOseekstominimizeamulti objective fitness parameter LDC = aL + bD + cC, where L is the transmission hop of the signal, D is the increase in conflict, and C is the cost of the extrahigh-powertransmitters.Constantsa,b,andcdefinetherelative weights of L, D, and C, respectively. L and D are computed from thescaledlengthandthescaleddegree,conceptsfromthesmall-world phenomenon. This algorithm has resulted in symmetric distributionof high-powertransmitters,improvednetworkperformance,andasaving in systemcost.

B. Mobile-NodePositioning

Lietal.haveproposedamixtureofstationaryandmobilenodesandparticleswarmgeneticoptimization(PSGO)asaremedytothecoverageholes[15].ThePSGOhybridisemployedtodetermineredeploymentpositionsofmobilenodesinordertoimproveaveragenodedensity.PSGOmaximizesqualityofservice,definedasthera- tio of the area covered to the total area of the ROI, $QoS = S_c/S$, which should be ideally equal to unity. The area covered $S_c$is $S_c = S_{nod}C\ \ S_{rob}C$, the union of the area covered by the station- ary nodes and the robot-assisted mobile nodes. $S_c$only depends on the sensing radius $r_s$and the positions (x and y coordinates) of the N mobile nodes, $S_c = f\ (x_{rob}1 \ldots x_{rob}N\ , y_{rob}1 \ldots y_{rob}N\ , r_s)$, whichPSGO determines. PSGO borrows the mutation and selection opera-tions from GA. In each iteration, PSGO discards some worst particles and generates an equal number of new particles at random locations. Besides,itmovesafewparticlesrandomly.Thepaperreportsashighas 6% increase in QoS with 5 out of 100 static nodes replaced bymobile nodes. Mobile nodes can be repositioned using PSGO dynamically as the network topology changes. However, it necessitates mechanisms for obstacle avoidance and location awareness.

1) VFCPSO: Wang et al. have proposed a virtual force coevolu-tionaryPSO(VFCPSO)fordynamicdeploymentofnodesforenhanced coveragein[16].Virtual-force-baseddynamicdeploymentinvolvesit- erativelymovingasensorbasedonvirtualattractiveorrepulsiveforces fromothernodes,obstaclesinthefield,andtheareasthatneedhigher coverageprobability.Virtual-forcevectorsdependonthedistancebe- tween nodes and whatever attract or repulse them, and their relative directions. A sensor's new positions are computed in such a way that itmovesinthedirectionofthevirtualforcebyastepsizeproportional to itsmagnitude.

In[16],a2n-dimensionalparticleirepresentsxandycoordinates of all n mobile sensor nodes: $X_i = \{x^1, x^2, x^1, x^2, \ldots\ x^1, x^2\}$.

The objective function

i1 i1
2 i2
in in

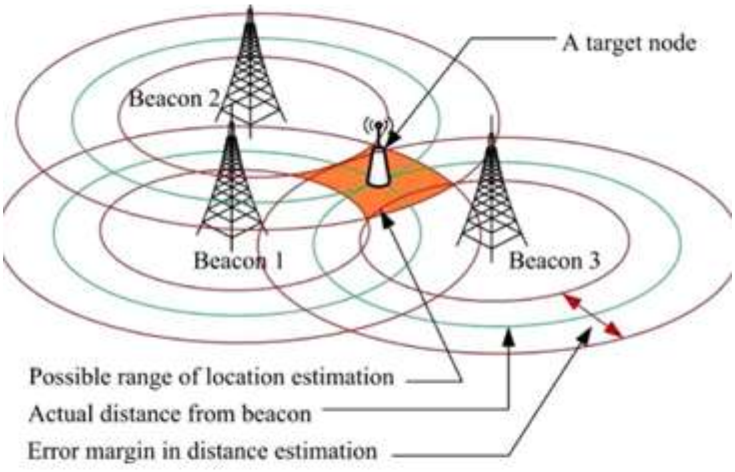

Fig. 1. Distance-based localization in a WSN.

$f(X_i)$ istheeffectivecoverage,whichthePSO maximizes.Inordertoachievebettercoverage,thePSOvelocityequa- tionismodifiedbyaddingtheterm$c_3r_3(k)g_{ij}(k)$to(1),where$c_3$isan accelerationconstant,$r_3(k)$isarandomnumberuniformlydistributed in[0,1],andg_{ij}isthesetofnewlocationsofnsensorscomputedusing virtual forces method. VFCPSO combines advantages of virtual force and PSO. Here, the 2n-dimensional PSO is converted into 2n single-dimensionalPSOs,eachconductedwithanindividualswarm.Thefinal solutionisproducedbyconcatenatingthe2ngbestsolutions.Authors reportsuperiorsensorcoveragewithsignificantlylessercomputational effort. The method involves significant energy expenditure in broad- casting initial and final positions. It also necessitates mechanisms for localization and collisionavoidance.

C. Base StationPositioning

Hong et al. have proposed PSO Multibase for optimal positioning ofmultiplebasestationsinatwo-tierWSN[17].Thetwo-tiernetwork consistsofnodesthatcancommunicateonlywiththeapplicationnodes they are assigned to. Application nodes possess long range transmit- ters, high-speed processors, and abundant energy. The PSO Multibase method aims at determining positions of base stations so that the total distanceofapplicationnodestotheirnearestbasestationsisminimum. This deployment requires minimum transmission power and assures maximum network life. In PSO Multibase, a particle i represents the positions of M base stations, which can be in two or three dimen- sionsbasedonthedeploymentterrain.Thefitnessofiisdefinedas

NODE LOCALIZATION INWSNS

Node localization refers to creating location awareness in de- ployed nodes [18]. Location information is used in geometric- aware routing [19]. An obvious method of localization is to equip each node with a global positioning system (GPS), which is not attractive because of cost, size, and power constraints. Many WSN localization algorithms estimate locations using a priori knowledge of the coordinates of special nodes called beacons,landmarks,oranchors.WSNlocalizationisatwophaseprocess.Inrangingphase,thenodesestimatetheirdistancesfrombeaconsusingsignalpropagationtimeorstrengthofthereceivedsignal.Signalpropagationtimeisestimatedthroughmeasurementoftimeofarrival, roundtriptimeofflightortimedifferenceofarrivalofthesignal[20]. Precise measurement of these parameters is not possible due to noise; therefore, the results of such localization is inaccurate as shown in Fig. 1. In the estimation phase, position of the target nodes is esti- mated using the ranging information either by solving simultaneous equations,orbyanoptimizationalgorithmthatminimizeslocalizationerror.PSOalgorithmsforWSNlocalizationaresummarizedinTableI.

A. Determination of Locations of TargetNodes

Gopakumaretal.haveproposedPSO-Locforlocalizationofn-target nodes out of m nodes based on the a priori information of locations ofm−nbeacons[21].Thebasestationrunsa2n-dimensionalPSO
(x and y coordinates of n nodes) to minimize the localization error

$j=1$ ij

Here, l_{ij}represents the total lifetime of the network, as computed

by l_{ij}= max $_{k=1}l_{i(k)j}$,thelifetimeoftheapplicationnode$j$that

defined as $f(x, y) = 1/M \sum^M \left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - \hat{d}_i\right)^2$.

Here,(x,y)isanestimateofthetarget-nodelocation,(x_i,y_i)isthe

$\sum_M$ $i=1$ i i i

communicates with the base station k. The lifetime $l_{ij}$is computed as

location of beacon node i, and $M \geq 3$ is the number of beacons in the

$l_{i(k)j}=e_j(0)/(r_j(\alpha_{j1}+\alpha_{j2}d^n_{(k)j}))$.Here,$d^n_{(k)j}$ representsthenth

neighborhoodofthetargetnode.Estimateddistancefrombeaconi,$\hat{d}_i$,

orderEuclideandistancefromkthbasestationtojthapplicationnode.

e(0) is the initial energy, and $\alpha_1$and $\alpha_2$are the distance independent anddistancedependentparametersthatdecidetheenergynecessaryfor the transmission, respectively. While both PSO Multbase andexhaus- tive grid-scan methods result in comparable lifetime, PSO converges in over 5 orders lesser time. The method is central and needs location awareness.Besides,thenodeshavetocommunicatetheirinitialenergy tothebasestation;thisenergyoverheadaffectsnetworkscalability.

1) Summary: Static deployment is a one-time process in which solution quality is more important than fast conver- gence. PSO suits centralized deployment. Fast PSO variants are necessary dynamic deployment. PSO can also limit network scalability.

is simulated as the actual distance corrupted by an additive Gaussian whitenoise.Thevarianceofnoiseinfluencesthelocalizationaccuracy. The approach does not take into account the issues of flip ambiguity andlocalizationofthenodesthatdonothaveatleastthreebeaconsin theirneighborhood.Theschemeworkswellonlyifeitherbeaconshave sufficient range, or there exist a large number of beacons. Moreover, the base station requires range estimates of all target nodes from all beacons in their neighborhoods. This requires a lot of communication that may lead to congestions, delays, and exhaustion of energy. In ad- dition, the proposed scheme has a limited scalability because the PSO dimensionality is twice the number of targetnodes.

1) PSO-Iterative: Kulkarni et al. have proposed a distributed iter- ativelocalizationalgorithmPSO-Iterativein[11].Eachtargetnode, which has three or more beacons in its hearing range, runs PSO to minimizethelocalizationerror.Nodesthatgetlocalizedactasbeacons forothernodes.Thiscontinuesiteratively,untileitherallthenodesget localized, or no more nodes can be. This method does not require that each node transmit its range measurement to a central node. Besides, it can localize all nodes that have three localized nodes or beacons in theirrange.Asthelocalizationiterationspassby,anodemaygetmore numberofreferencesforlocalization,whichmitigatetheflipambiguity problem, the situation that results in large localization error when the references are near collinear. However, the proposed method is prone to erroraccumulation.

2) PSO-Beaconless:Lowetal.haveproposedin[22]aPSO-based distributed-localization scheme that does not involve beacons. The nodes are deployed by an unmanned aerial vehicle equipped with a position sensor. The exact location $\Phi_i$of a node i is treated as the conditionalprobabilitydensityfunctionofΦ_{di},thelocationwherethe nodeisdeployed(whichisrecordedbytheuseofapedometer).Ifthis node can receive a signal from a localized node j, it can estimate its distance d_j. A likelihood function for exact location is expressed in terms of $\Phi_{di}$and d_j. PSO minimizes one term of this likelihood func- tion.Theresultsoftwovariantsofthealgorithmarepresented.Results show fairly accurate localization even in sparse deployment. Authors report the results of real-time field tests of an implementation of the PSO-beaconlessalgorithmonalow-costMicrochip-PIC18LF4620mi- crocontroller [23]. It is reported that PSO takes longer computational time, but performs as accurate localization as the Gauss–Newton al- gorithm does when the pedometer accuracy is high. However, in less accurate pedometer records, the PSO outperforms the Gauss–Newton method in terms of localizationaccuracy.

3) PSO-4 Beacon: Low et al. have proposed PSO-4 Beacon lo- calization scheme in [24]. This scheme assumes a presence of four beaconsdeployedroughlyonboundariesofthesensorfield.Alltarget nodes can receive the signals from the beacons deployed at positions A, B, C, and D. A node at location O in the sensor field canestimate

itsdistancefromabeaconas$d=(P/P_0)^{-\frac{1}{\alpha}}$,wherePisthepowertransmittedbythebeaconandP_0isthepoweratunitdistanced $_0$.Envi- ronmentalpathlossexponentαplaysanimportantroleinthedistance

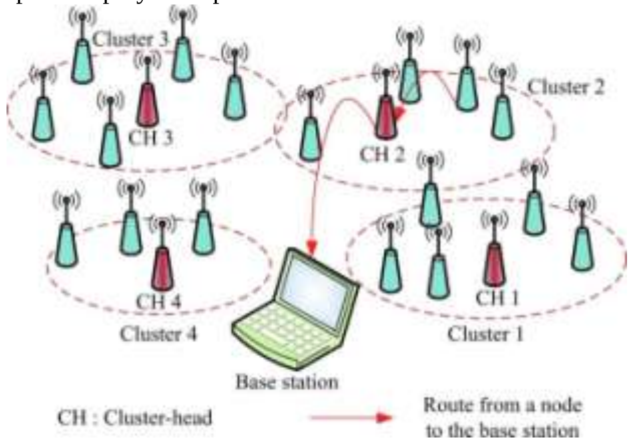

Fig. 2. Structure of a clustered WSN.

calls for an optimal cluster-head election mechanism. Besides, clus- ter assignment influences network performance and longevity. Low- energy-aware clustering hierarchy (LEACH) is a simple and efficient algorithm[25].ClusteringisanNP-hardoptimizationproblem,which PSO can handle efficiently. Clustering or cluster-head selection is not a one-time activity; therefore, the simpler the optimization algorithm, the better the network efficiency is. This is another reason why PSO is a popular choice for WSN clustering. A summary of recent PSO applications in WSN clustering is given in TableI.

1)PSOClustering:Guruetal.haveproposedfourvariantsofPSO,namely,PSOwithtimevaryinginertiaweight(PSOTVIW),PSOwithtimevaryingaccelerationconstants(PSO-TVAC),hierarchicalPSO-TVAC(HPSO-TVAC),andPSOwithsupervisorstudentmode(PSO- SSM)forenergy-awareclusteringin[26].PSOassigns$n_j$nodestoeachofthekclusterheads,j=1,2,...,k suchthatthetotalenergylossduetophysicaldistancesE_{dd}isminimum.Thisisdefinedin(3), where$D_j$isthedistancebetweencluster-headjandthebasestationestimation from the received signal strength. In the scheme proposed in [24], the target node at location O localizes by solving geometrical

k nj

F =

2

2 j

ij

nj

. (3)

- d + Σ D

equationsifthevalueofαisknown.ThetargetnodeusesPSOtofindthebestvalueofαandusesaKalman-filter-basedrecursiveestimation tolocalizeitself.Thepaperreportsfairlygoodlocalizationaccuracy.4) Summary: Localization is a one-time optimization process in which solution quality is more important than fast convergence. Dis- tributed localization is desirable due to energy issues. Though PSO is appropriate for distributed localization, the choice is influenced by availability of memory on thenodes.

ENERGY-AWARE CLUSTERING (EAC) IN WSNS

EconomicusageofenergyisacriticalissueinWSNs.Communi-cation is the most energy-expensive activity a node performs. Energy required to transmit varies exponentially with transmission distance; therefore, it is customary to use multihop communication in WSNs. A WSN's lifetime largely depends on how efficiently it carries a data packetfromitssourcetoitsdestination.Routingreferstodetermining a path for a packet from a source node to a sink. The WSN that uses hierarchical routing has its nodes clustered into groups. Each cluster has a node that acts as the cluster head. Nodes that belong to a clus- ter transmit their data packets to the cluster head, which forwards it to the base station as shown in Fig. 2. A node that acts as a clus-terheadforalongdurationexhaustsitsbatteriesprematurely.This

j =1 i=1

In PSO-TVIW, the inertia weight w is decreased linearly in each iteration.InPSO-TVAC,inertiaweightissetconstant,andacceleration constants $c_1$and $c_2$are varied linearly in every iteration. In HPSO- TVAC,theparticleupdateisnotinfluencedbythevelocityinprevious iteration; but, reinitialization of velocity is done when the velocity stagnates in the search space. Finally, in PSO-SSM, the PSO-update equation is modified to (4), where mc is a constant called momentum factor. Clustering is based on a simple idea that for a group of nodes thatlieinaneighborhood,thenodeclosesttothebasestationbecomes the cluster head. A detailed comparative analysis of the algorithms for optimal clustering is presented. This scheme considers only the physicaldistancesbetweennodesandtheirassignedclusterheads,but not the energy available to thenodes

$X_{id}(k+1)= (1-mc)X_{id}(k)+mcV_{id}(k+1)$. (4)

2) PSOC:Latiffetal.considerbothenergyavailabletonodesandphysicaldistancesbetweenthenodesandtheirclusterheadsin[27].Eachparticlerepresentsacombinationofclusterheads.ThefitnessfunctionforthecentralizedPSO(PSO-C)isdefinedas$f=\beta f_1+$ $(1\beta)\mathbf{f}_2$,where$\mathbf{f}_1$isthemaximumaverageEuclideandistanceofnodestotheirassociatedclusterheadsand$\mathbf{f}_2$istheratiooftotalinitial energy of all nodes to the total energy of the cluster-head candidates. These are expressed as (5) and (6), respectively.

Theauthorspresentnumericalresultstoshowthatthepowerscheduledeterminedby PSOresultsinsubstantialenergysavingsincomparison totheuniformpowerschedule,especiallyincaseofalargenumberof

$f_1=$ max

$\{\Sigma$

$_i d(n_i, CH_{p,k})$ }
(5)
nodes.
k=1,2,..K ⌊ $\forall n \in C$
p, k
$|C_{p,k}|$ ⌋
B. Determination of Optimal-LocalThresholds
N ∑
f= i =1 ∑
$E(n_i)$

(6)
In binary hypothesis-testing, distributed sensors make a binary (0
2 K
k =1
$E(CH_{p,k})$
or 1) decision using local thresholds and send their decisions to a neighboring node. In a parallel-fusion architecture, all nodes send their

where N is the number of nodes out of which K will be elected as the cluster heads. $C_{p,k}$is the number of nodes that belong to cluster $C_k$in particle p. This ensures that only the nodes that have above-average energy resources are elected as the cluster heads, and that the average distance between the nodes and the cluster heads is minimum. They compare the results of the algorithm with those ofLEACHandtheLEACH-Calgorithms[28].ThePSO-basedclustering outperforms both LEACH and LEACH-C in terms of the network lifespanandthethroughput.In[9],Latiffetal.showthatthisPSO-based algorithmoutperformsGAandK-means-basedclusteringalgorithmsas well.

3) MST-PSO:Caoetal.haveconsideredaninterestingcaseinwhich anodeanditscluster-headengageinamultihopcommunication[29]. Themethodcomputesadistance-basedminimumspanningtreeofthe weighted graph of the WSN. The best route between a node and its cluster-head is searched from all the optimal trees on the criterion ofenergyconsumption.Clusterheadsareelectedbasedontheenergy availabletothenodesandtheEuclideandistancetoitsneighbornodein theoptimaltree.Theauthorscomparetheperformancesofthreemech- anismsofcluster-headelection:energybased,auto-rotationbased,and probabilitybased.Routingandcluster-headrotationaretreatedasop- timization problems and tackled through PSO. The results show that the PSO-based clustering methods ensure longer networklife.

4) Summary: Optimal clustering has a strong influence on the per-formanceofWSN.Clusteringisacentralizedoptimizationcarriedout in a resource rich base station suitablefor.

DATA AGGREGATION INWSNS

Largescaledeploymentofsensorsresultsinvoluminousdistributeddata.Efficientcollectionofdataiscritical.Dataaggre gationisthepro-cessofcombiningthedataoriginatingfrommultiplesourcessuchthat theresultisbetter(moreconcise,morereliable,etc.)orthecommuni- cation overhead is reduced [30]. A major application of a distributed WSNistodetectanevent.Indecentralized-detectionframework,each sensornodecollectslocalobservationscorruptedbynoiseandsendsa summary (compressed or partially processed data) to a fusion center. Thefusioncenterusesthesametomakethefinalglobaldecision.This ensures an extended network lifespan at the expense of a reduction in performance. PSOhasprovidedoptimizationinseveralaspectsofdata aggregation as summarized in TableI.

A. Optimal Transmission Power Allocation

Thewirelesschannelcommontothenodesandthefusioncenterundergoesfading,whichinfluencestheaccuracyoffusion .Itisshownthat the transmission power-allocation scheme for distributed nodes plays an important role in the fusion-error probability. Wimalajeewa et al. address the problem of optimal power allocation through constrained PSO in [31]. Their algorithm PSO-Opt-Alloc uses PSO to determine optimal-power allocation in the cases of both independent and corre- latedobservations.Theobjectiveistominimizetheenergyexpenditure while keeping the fusion-error probability under a required threshold.

decisions to a base station; and in serial architecture, decisions follow a hop sequence from the first node to the base station. Threshold- ing leads to a gain in terms of bandwidth and energy, and a loss in terms of accuracy.

Optimal thresholds on all nodes and an optimal- decision route (called hierarchy) assure minimum energy expenditure and maximum accuracy. Veeramachaneni et al. present a hybrid of ant-based control and PSO (ABC-PSO) for hierarchy and threshold management[32].Inant-basedoptimization,artificialantsmovefrom a node to another constructing a partial solution to the problem. Once anantreachesthefinalnode,theperformanceofthesolutionisevalu-atedandthepathemphasizedusingamathematicalvalueproportional to its performance (called pheromone). In ABC-PSO algorithm, ants constructthesequenceandPSOidentifiesthethresholdsandachieves the minimum error for the sequence. A feedback on this is presented to ants to help them move in the search space and identify better sequences.

C. Optimal SensorConfiguration

Multisensor systems consist of several sensing options and configurations. Adaptive configuration of the system having var- ious sensor resources and multiple sensor parameters is a multiobjective optimization problem. Objectives generally in- clude maximum accuracy, minimum usage of communica- tion resource, and maximum sensing coverage. Veeramachaneni etal.presentabinarymultiobjectivePSOBMPSOforoptimalconfig-urationin[33].ThismethodusesBayesiandecision-fusionframework to fuse the decisions from multiple sensors. Swarm agents are used to evolvethechoiceofsensors(eachagentisasubsetofsensorsusedfor fusion).EachagentevokesPSOtoevolvethethresholdsandoptimum fusion rules for its sensor set. The results highlight agents' ability to decide an optimal configuration of sensors, their thresholds, and the optimal-fusionrule.

1) Summary: Data aggregation is a distributed repetitive process moderately suitable for PSO. Effective data aggregation influences overallWSNperformanceanddemandsquick-convergenceoptimiza- tion techniques that assure high-quality solutions. PSO is moderately suitable for thischallenge.

II. Conclusion

Scale and density of deployment, environmental uncertainties, and constraints in energy, memory, bandwidth, and computing resources poseseriouschallengestothedevelopersofWSNs.Issuesofthenode deployment, localization, energy-aware clustering, and data aggrega- tion are often formulated as optimization problems. Most analytical methods suffer from slow or lack of convergence to the final solu- tions. This calls for fast optimization algorithms that produce quality solutions utilizing less resources. PSO has been a popular technique used to solve optimization problems in WSNs due to its simplicity, high quality of solution, fast convergence, and insignificant compu- tational burden. However, iterative nature of PSO can prohibit its useforhigh-speedreal-timeapplications,especiallyifoptimization needs to be carried out frequently. PSO requires large amounts of memory, which may limit its implementation to resource-rich base stations. Literature has abundant successful WSN applications that exploit advantages of PSO. Data aggregation needs frequent dis- tributed optimization and fast solutions. Thus, PSO moderately suits it. Static deployment, localization, and clustering are the problems solved just once on a base station; thus, PSO highly suits them. Fu- ture research on PSO in WSN applications is likely to focus on the following.

1) Transformation of existing simulations into real-world applica- tions.
2) Development of PSO inhardware.
3) Development of parameterless black-boxPSO.
4) Cross-layer optimization throughPSO.

An overview of PSO, issues in WSNs, and a brief survey of recent PSO-based solutions to the WSN issues are presented in this paper. AdvantagesandlimitationsofPSOhavebeenpointedout.Aqualitative discussion on how PSO is tailored for WSN applications ispresented, and promising research directions are projected. From the current rate of growth of PSO-based applications, it is envisioned that PSO will continueasanimportantoptimizationtechniqueinseveralengineering fields includingWSNs.

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