Consensus-based Data Aggregation for Wireless Sensor Networks

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Abstract: The paper addresses the application of consensus-based methods for agreement within networks of embedded computing and communication devices. A thorough literature review is carried out from both theoretical and practical perspectives while proposing a consensus aggregation mechanism for effective information processing in wireless sensor networks. The aim is to reduce the communication and energy burden at the cluster level, while improving the quality of the aggregated information. Building on an extensive theoretical background, a practical approach is favored in order to realistically model the impact of the consensus algorithms on the sensing entities, using well-adopted tools. Extensions are considered towards including sensor node mobility and large scale monitoring supported by cooperative UAV swarms. Simulation results are discussed from a comparative standpoint.

Keywords: data fusion, sensor fusion, cooperative aggregation, wireless sensor networks, consensus algorithm, convergence analysis.

1. INTRODUCTION

Dense networks of embedded heterogeneous devices for system monitoring and control have emerged. These are represented generically by networked control systems (NCS) and multi-agent systems (MAS) and can be effectively implemented by wireless sensor and actuator networks or robotic swarms: ground, aerial, surface, underwater, etc. Such systems of systems aim at achieving the goal of distributed, pervasive control at a local scale, without the direct action of a central coordination entity. The salient advantages reside in local awareness of process or target state at high spatial and temporal resolutions and higher capability for failure detection and robustness. However, challenges have to be overcome in eliminating redundant information across the network while offering complete and correct updates to all the nodes participating in the decision process. In this manner, both over-communication and information starvation can pose problems which have to be mitigated as efficient as possible.

We focus on distributed decision among networks of intelligent sensor nodes while accounting for their computing, communication and energy restrictions, e.g. the TelosB mote, one of the more popular WSN platforms, uses a 16-bit MCU without floating point capability along with a low-power ISM band radio transceiver and limited memory (<8kB). The main expected impact of this work concerns reducing the overall communication latency, avoiding bottlenecks which lead to energy waste for battery operated devices, by exploiting locally available computing and adaptive algorithms. Depending on the network topology assumptions simulation parameters can be adjusted. For example, a fully connected, time-invariant network is easy to model and analyse in simulation but such assumptions do not hold true in real deployments where the spatial distribution of the nodes might impede communications and low-power radio links exhibit stochastic and asymmetric behaviour. One relevant tool in this case are Monte Carlo methods which have been generally applied to achieve complex systems simulation under probabilistic parameter variations for reliable deployments (Mahmood et al., 2015).

The targeted problem within this paper is analysing the best way to achieve local agreement in dense wireless sensor network deployments, used both for higher level supervisory decision support and local control. Consensus algorithms are a promising class of mathematical methods which can provide optimal outcomes under strict convergence and performance bounds in such cases. The underlying challenge can be split in two parts. *What is the "best" way to organize the exchange of information at a network and cluster level by scheduling message exchanges at a static or dynamic rate i.e. event-based? What is the "best" way for each individual node to incorporate received information from its neighbours along it's own measurements which is both correct and contributes to overall convergence in as few iterations as possible?*

Consensus problems in wireless sensor networks can be classified according to the complexity of the in-network information processing schemes. These range from simple binary agreements i.e. jointly deciding that a local temperature value is out-of-bounds and alerting the sink, local averages to compensate for low-cost sensor calibration and measurement errors in improving positioning accuracy for mobile nodes, up to distributed least mean squares (D-LMS) schemes which provide sound optimal estimates.

The paper is structured as follows. Section two carries out a timely review of consensus algorithms applied to multi-agent deployments. Both theoretical and practical/implementation details relevant to wireless sensor networks are surveyed. Section three presents the system architecture to apply consensus-based constrained aggregation algorithms leading to intelligent reduction of the communication and energy burden upon the sensing nodes. In Section 4 simulation results are presented in a comparative manner with focus on both convergence and iterative algorithm performance. Section 5 concludes the paper and outlines perspectives on future work.

2. REVIEW OF CONSENSUS-BASED METHODS

2.1 Theoretical Background

The common approach in establishing the theoretical background for the distributed consensus algorithms is based on graph theory. This assumes the modelling of the system of systems as composed of multiple communicating entities, through a graph with vertices and edges with constant or time-varying topology. Thus, the directed graph $\mathcal{G}_n = (\mathcal{V}_n, \mathcal{E}_n)$, with the node set $\mathcal{V}_n = \{1, \dots, n\}$ and edge set $\mathcal{E}_n \subseteq \mathcal{V}_n \times \mathcal{V}_n$ is considered. For time-varying communication channels the time-dependant connectivity graph is introduced with $\mathcal{G}_n(t) = (\mathcal{V}_n, \mathcal{E}_n(t))$ where $\mathcal{E}_n(t)$ is the set of active edges at time *t* (Lin et al., 2005).

The generic continuous consensus algorithm for updating the information state $x_i(t)$ of node *i*, can be formulated as:

$$\dot{x}_i(t) = -\sum_{j=1}^{n} a_{ij}(t)[x_i(t) - x_j(t)] \quad (1)$$

Achieving consensus implies that for all $x_i(0)$ and all $i, j = 1, \dots, n$, $|x_i(t) - x_j(t)| \longrightarrow 0$, when $t \longrightarrow \infty$. a_{ij} are positive weights in the case that $(i,j) \in \mathcal{E}_n$ and $a_{ij} = 0$ otherwise which correspond to the elements of the adjacency matrix $A_n \in \mathbb{R}^{n\times n}$ of the communication graph. In matrix form, consensus is expressed as:

$$\dot{x}(t) = -\mathcal{L}_n(t)x(t) \quad (2)$$

Where is the non-symmetric Laplace matrix of the directed graph, with $l_{ii} = \sum_{j=1, j\neq i}^{n} a_{ij}$, $l_{ij} = -a_{ij}, i \neq j$.

The discrete version, for communication at discrete time instants is expressed in similar manner:

$$x_i[k+1] = \sum_{j=1}^{n} d_{ij}[k]x_j[k] \quad (3)$$

with the consensus condition that for all $x_i[0]$ și pentru toate $i, j = 1, \dots, n$, $|x_i[k] - x_j[k]| \to 0$, $k \to \infty$ (Wei et al., 2005).

Main challenges concern convergence analysis and estimation of the equilibrium state after consensus has been reached. Previous results show that consensus is reached if the symmetric communication topology is connected. Also based on algebraic connectivity analysis of the underlying communication graph, the convergence performance can be estimated for various pre-conditions. The equilibrium state is typically a weighted average of the initial information states of the network nodes where not all nodes have to contribute.

Stability has been analysed in (Moreau, 2004) where the approach favours the decomposition of complex systems into networks of simple sub-systems with basic dynamic e.g. single integrator, leading to mild convergence conditions. (Moreau, 2005) extends the work towards a multi-agent systems paradigm in time-varying communication topologies and points out that excessive information exchange between agents can potentially disrupt the agreement mechanism.

Concerning robust consensus for wireless sensor networks, weight selection for information state update with time-variant communication is discussed by (Lin et al., 2005). It addresses the particular case of average consensus, i.e. all nodes influence the final result in equal proportion. Main finding is the evaluation of consensus properties in time-varying graphs based on two types of weights on the edges: maximum-degree and Metropolis. The weight matrix for the latter case is expressed as:

$$W_{ij}(t) = \begin{cases} \frac{1}{1+\max\{d_i(t), d_j(t)\}}, \{i,j\} \epsilon \mathcal{E}(t) \\ 1 - \sum_{\{i,k\}\in\varepsilon(t)} W_{ik}(t), i = j \\ 0 \end{cases} \quad (4)$$

The weight of each communication link for each node is periodically updated using the number of transmissions and the out-degree value. It is shown how, by using this type of weight matrix, the convergence speed of the algorithm increases, especially for denser networks and asymmetrical graphs. Performance is analysed by evaluating the Mean-square Errors (MSE) in conjunction with the optimal Maximum Likelihood (ML) estimation error. The scheme can be seen as a particular case of distributed optimization for sensor networks and extend the problem towards multi-sensor fusion where each node samples several measurements with various time steps.

Analysed from a signal processing perspective, consensus is evaluated with several probabilistic models for link noise and connectivity. By modelling link failures and channel noise in a stochastic framework (Kar et al., 2009), statistical properties of the convergence process are derived using Monte-Carlo simulation. (Saed et al., 2010) applied the above-mentioned Metropolis weighting scheme to study convergence under several error models of the communication links. The number of iterations needed to achieve consensus is used as performance metric. (Mateos et al., 2009) and (Schizas et al., 2009) present work on the distributed Least Mean Squares (D-LMS) for consensus, in-network adaptive estimation for sensor networks. Beyond MSE, the excess mean-square error (EMSE) and mean-square deviation (MSD) are used as performance metrics for single-hop bidirectional communication among nodes. D-LMS involves the computation of simple recursion functions at each node while the analysis covers both stationary and non-stationary cases and concludes that, while in the former the reduction of the step size yields improved steady state error, the time-varying model requires the computation of an optimal step size, with a too small value not allowing the algorithm to adapt to the variations. The network topology includes a subset of “bridge” sensors to relay information across the network and numerical examples are provided for both ideal and noise cases based on the normalized estimation error in relation to a reference system. Distributed LMS-type adaptive algorithms for tracking yield close outcomes compared to the centralized approach.

2.2 Implementation

Several practical implementations in simulation or experimental are discussed next to establish a context of current applications. In the case of event detection applications, some works have discussed and implemented binary consensus where the information state agreement is either zero or one. In this case the nodes decide locally on the truth value of a supposition e.g. temperature over a certain threshold, followed by agreement among neighbouring nodes (Abderrazak et al., 2013). Four states are defined, reflecting the node's opinion on the majority belief, as: 0 – most likely false, e_0 – might be false, e_1 – might be true and 1 – most likely true. Following discrete iterations by message exchanges, convergence is achieved when all nodes have either states 0, e_0 or states e_1 , 1 using the pre-defined rules:

$$(0, e_0) \rightarrow (e_0, 0)\ (0, e_1) \rightarrow (e_0, 0)\ (0,1) \rightarrow (e_1, e_0)$$
$$(e_0, e_1) \rightarrow (e_1, e_0)\ (e_0, 1) \rightarrow (1, e_1)\ (e_1, 1) \rightarrow (1, e_1)$$
$$(s, s) \rightarrow (s, s)\ s = 0, e_0, e_1, 1 \tag{5}$$

Simulation results for various network topologies, using JTOSSIM are presented in (Abdaoui et al., 2013). Detailed algorithm description and convergence time analysis is also carried out by (Al-Nakhala et al., 2015) in both simulation and test bed deployment.

From an implementation point of local average consensus, (Avrachenko et al., 2011) present a neighbourhood algorithm for trust weight estimation and numerical simulation results for various graph topologies such as 2-clique graphs, Watts-Strogatz graphs and random geometric graphs. Evaluation is performed based on convergence time and relative error. Actual implementation on a network of IRIS motes under TinyOS has been done by (Kenyeres et al., 2011). A very interesting perspective is analysing the influence of the limitation in the timer precision and local computation accuracy on the outcome of the consensus algorithm.

Consensus has been also recently applied for building energy management based on occupancy and cost constraints. (Gupta et al., 2015) describe a consensus framework which carries out agreement among users of a building and the BMS controller. A central coordinator is employed to collect user preference and current state and generate the consensus value. This leads to establishing the zone-level temperature set point, converging to the minimum cost temperature vector for the building. The distributed optimization stage and associated convergence is carried out by means of the proposed Alternating Direction Method of Multipliers (ADMM) introduced in (Boyd et al., 2011) to compute the optimal set-points. A positive/negative penalty mechanism is used to drive users towards the consensus equilibrium point. Control synthesis leverages a conventional heat transfer model for the control law design which is afterwards validated in a virtual test-bed.

Another active application area suitable for consensus algorithms is the cooperative control of multi-vehicle robotic systems like UAV and USV swarms (Jaimes et al., 2010). Objectives can include rendezvous problems under uncertainty, formation maintenance, cooperative non-overlapping area surveillance and data collection from a network of ground sensor nodes (Stamatescu et al., 2015). Such applications can be assimilated to mobile sensor network models with time-varying asynchronous communication.

Practical environmental monitoring consensus among sensor nodes is described by (Contreras et al., 2014) on a network of Sun SPOT nodes. After network formation, the nodes reach consensus by calculation the trust factor matrix of the network topology at each discrete time step. Convergence is guaranteed by the fact that the dynamic of the monitored process e.g. temperature is slower than the convergence time of the algorithm. (Li et al., 2013) introduce a two-tiered, clustered model for a localized gossip algorithm to improve consensus accuracy after a pre-determined number of iterations. Various clustering techniques are analysed and a utility function is used to account for the number of iterations and relative error.

(Elbhiri et al., 2009) present simulation results leveraging the Castalia simulator built on top of the OmNET++ framework. Evaluation for various power level is also carried out. (Choi et al., 2012) present a compressive sensing approach to model the degree in which the information of each node is of relevance to the final consensus.

(Manfredi, 2013) presents the design of a dynamic consensus algorithm for multi-hop WSNs in networked control systems for industrial applications. Main contribution is extending the 2-hop consensus model by (Jin et al., 2006) to an m-hop model as follows:

$$\dot{x}_i = -k_i \sum_{k \in N_i} w_{ik} \left(x_i(t-\tau_{ii}) - x_k(t-\tau_{ik}) + \sum_{t \in N_\mathrm{k}} w_{kt}\big(x_i(t-\tau_{ii}) - x_t(t-\tau_{it})\big) + \cdots \right) + \dot{z}_\iota \tag{6}$$

where τ_{ik} is considered the time delay between one-hop neighbors i and k and similarly τ_{it} is the time delay between two-hop neighbors i and t and so on. The vector $\dot{z}_\iota = [\dot{z_1}, \dots \dot{z_n}]^T$ represents the variations of the sensor inputs.

The proposed method allows direct integration of node information using all the nodes at distance m from the aggregation centre, taking into account the network latency. Departing from theoretical issues and system modelling, the implementation uses a ZigBee network and AODV routing, by piggybacking the standard HELLO packets of the routing protocol with the state information for each node. The experimental results show the impact of the system gain K and message frequency f_H on system asymptotic stability and performance.

Finally, extensions to other domains include achieving particle swarm optimization for improving network coverage by means of particle speed consensus (Loscri et al., 2012).

Performance of the method is established by using both global and local objective functions. Target tracking by means of belief functions is presented in (Savic et al., 2014) where five methods are comparatively analysed: standard belief consensus, randomized gossip, broadcast gossip, Metropolis belief consensus and a new algorithm based on belief propagation. Main findings suggest the method choice based on network topology and include the usage of Metropolis belief consensus in loopy networks while belief propagation is more suitable for tree networks.

3. CONSENSUS-BASED AGGREGATION FOR LARGE SCALE COOPERATIVE HETEROGENEOUS MONITORING

Beyond the current context, we aim at leveraging the state-of-the-art for achieving data aggregation in hierarchical networks of cooperative entities based on wireless sensor network for large scale monitoring. Our reference application consists of dense heterogeneous networks for critical infrastructure surveillance of road and pipeline transport systems. The high level system architecture, previously introduced in assumes ground-level, UAV-supported, sensor data collection and relaying to a central control centre which supervises the monitoring system. The system architecture is illustrated in Figure 1.

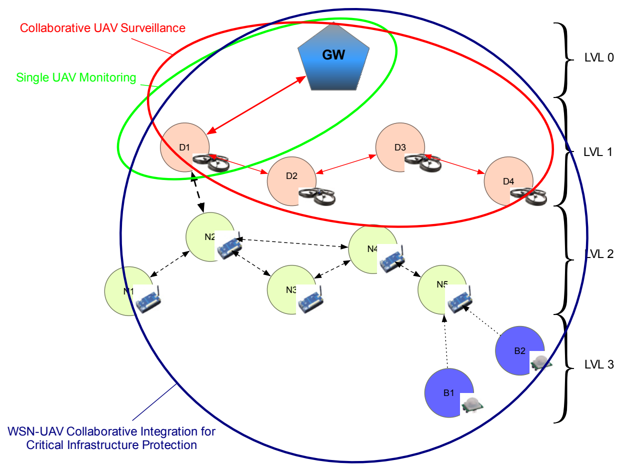

Fig. 1. Collaborative large-scale monitoring and control architecture based on WSN-UAV integration (Stamatescu et al., 2014).

The multi-level structure described starts from simple binary detectors connected to the multi-hop mesh sensor network for ground data collection and processing. At the upper levels, aerial robotic platforms, acting independently or in swarms collect rich information regarding the target environment but also relay the WSN data towards the control centre gateway. At the top level, humans enter the loop by supervising the distributed system with the help of a decision support framework. The operational scenarios listed in the proposed structure range from basic single UAV monitoring, to collaborative UAV surveillance, up to integrated collaborative WSN-UAV for complex assignments.

In this scenario, consensus is viewed as a tool for local data aggregation, with the final value being relayed upstream towards higher decision levels. Local sensor node clusters agree on the common value of interest and then relay it upstream through the cluster head. Parameterization of the consensus process includes among others: the communication model (time invariant/variant, impact of asymmetric links and TX/rx probabilities), the mobility model (with fixed and mobile nodes) and dynamic adjustment of the weight matrix for computing the local estimates at each node. Values of interest, reflected by the scalar or multi-dimensional state information of each node, may include: event confirmation, environmental parameters, vibration, other types of process variables (pressure, flow, etc.).

The conventional approach for large scale interconnected system or systems of systems, usually holds true in the case of consensus-based methods as well. Each node of the network is dynamically modelled along with an additional model describing the interactions to/from his peers. In this case, the basic technique leverages single or double integrator dynamics at each node, with potential extensions aimed at nonlinear system modelling. For simulation of our approach two tools are used: MATLAB Toolbox for Interconnected Dynamical Systems - MTIDS (Deroo et al., 2013), integrated with SIMULINK and Mathgraph tool for complete modelling and simulation. Another implementation, of dynamic consensus is applied for analysing distributed least mean squares (D-LMS) problems for mobile sensor networks.

Distributed information processing in this type of applications brings attractive properties to the monitoring and control systems, such as: mitigating communication bottlenecks, robust fail-safe operation and scalability. Challenges stem from global awareness across the aggregation entities to avoid redundancies. We see data aggregation as the first step towards sensor fusion, where multi-scale, multi-domain signals can be effectively combined for real-time oversight. Probabilistic sensor/data/information fusion has been previously applied for target identification and tracking, compensating for sensor inconsistencies and failure and leveraging long range, high-bandwidth communication links. This represents a set of key methods to enable the 4C: computing, communication, control and cognition paradigm.

Having described the nature and constraints of our application, the main contribution of this work, within the state-of-the-art, is the evaluation of the suitability of these methods in a given context for improving network information flow and assisting the human operator at the network control centre in a decision support framework. We used a reference twenty node, medium size, wireless sensor network to establish convergence and study its properties. Several representative use cases have been defined based on modelling the network graphs associated to the communication topologies. Our simulation results are carried out using MATLAB environment but other have been considered from generic network simulators: OmNET++, ns3 to operating systems for resource constrained devices and their associated simulation tools such as TinyOS with TOSSIM or Contiki and COOJA which can be suitable for particular application requirements and constraints.

4. SIMULATION RESULTS

4.1 Modelling/Simulation for average consensus

Two simulation scenarios have been initially defined: random graph with undirected links and directed links. The reference topology for the undirected sensor network communication graph is shown in Figure 3 along with the MTIDS toolkit user interface.

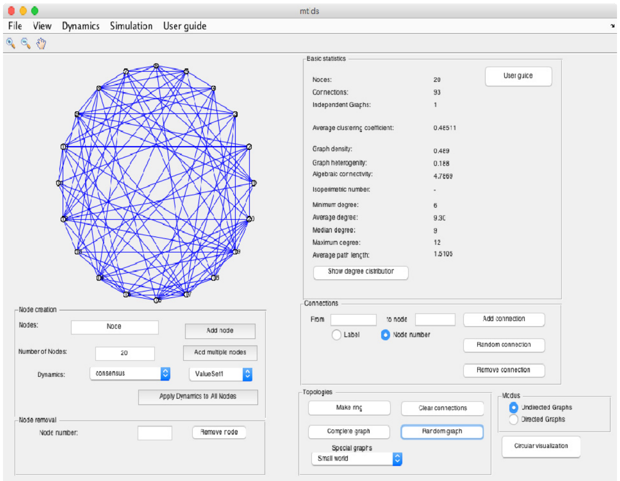

Fig. 2. Random directed graph model and MTIDS UI.

Table 1 list the quantitative graph parameters relevant to the analysis. Per theoretical previous results, we are able to evaluate convergence speed based on the algebraic connectivity indicator. In this situation the graph is well connected and offers good performance in a time invariant communication channel model. Other key indicators include the graph density, heterogeneity and the average path length.

Table 1. Case 1 – Random *undirected* graph

Nodes	20	**Algebraic connectivity**	4.7869
Connections	93	**Minimum degree**	6
Independent graphs	1	**Average degree**	9.3
Average clustering coeff.	0.48511	**Median degree**	9
Graph density	0.489	**Maximum degree**	12
Graph heterogeneity	0.188	**Average path length**	1.5105

Figure 3 plots the statistical node degree distribution for the random model with the associated probabilities at the node level. The indicator can be used in conjunction with the selection of the routing algorithm to exploit high connectivity nodes as mesh routers inside the local cluster. By dynamically adjusting the corresponding the probabilities, the model can be extended to a time-varying one, enabling the analysis of random communication channels, prone to symmetric interference.

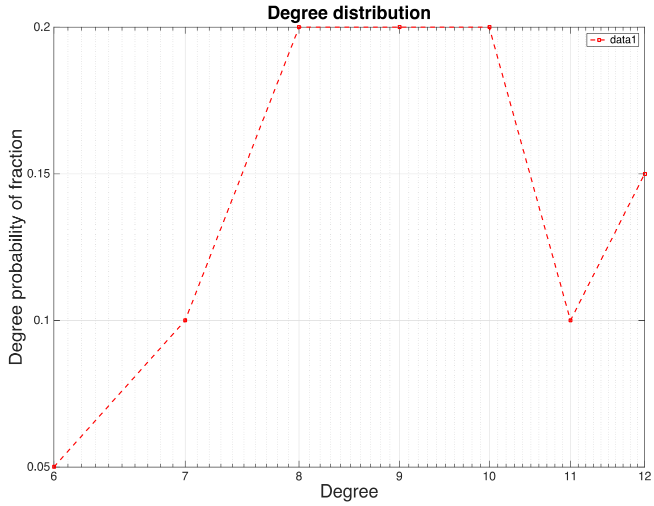

Fig. 3. Degree distribution.

The main result of case 1 is illustrated in Figure 4. It can be seen how from initial information states uniformly distributed across a given interval, the twenty nodes converge by information exchange and consensus. Convergence time in this case is around 14 seconds. As anticipated, the convergence rate is higher for the first iterations then pointing asymptotically to the equilibrium value, in this case zero. Convergence at each node is evaluated by thresholding the performance metric, e.g. the mean squared error (MSE), after which a stop condition is triggered.

$$MSE = \frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{n-2} \tag{7}$$

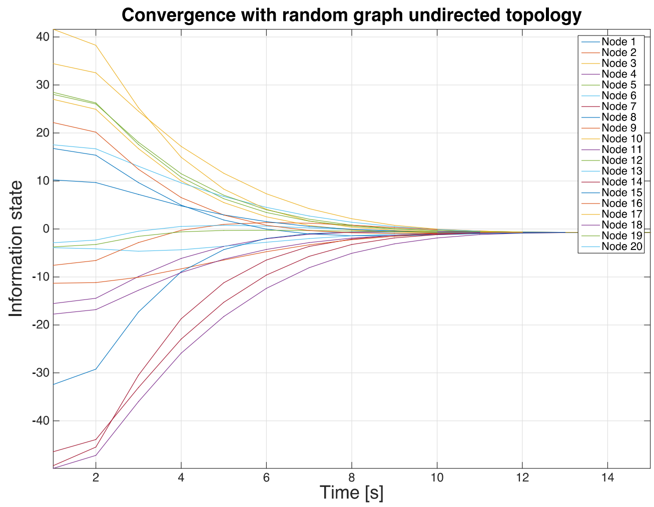

Fig. 4. Convergence analysis for case 1.

The first described case of random undirected graphs serves as support for basic convergence behaviour of the consensus algorithm. The system can be tuned for performance by increasing the sampling and communication rate along with the system gain to the stability limit. Also, the simulation environment supports large scale interconnected LTI system modelling with the same communication network topology graph.

For the second case that we analyse, a small-world model random directed graph is considered. This provides some insight into the behaviour of sensor networks with time-varying unreliable and asymmetrical links at a give discrete time step t. The small world graph model assumes the distance between randomly chosen nodes L to grow proportionally to the logarithm of the number of nodes N.

$$L \propto logN \quad (8)$$

The graphical representation in Figure 5 has been generated using the coefficients: 0.1 for the probability of a random edge and a 0.8 for oppositeness. Most neighbours are not neighbours (indicator set to 2) but each one can be reached in a small number of hops.

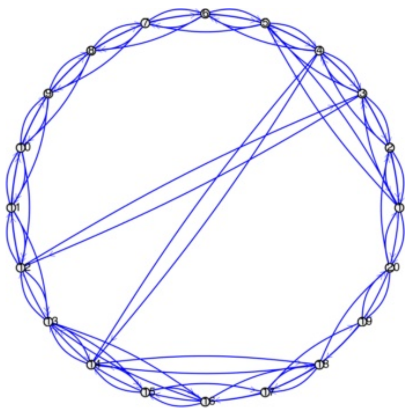

Fig. 5. Small-world random directed graph model.

Table 2 lists the key properties of the small-world random directed graph model. Specific properties related to directed graphs are included such as spanning trees, balancing and in-out degrees for the nodes. The number of connections in this case is lower than for the first one and the average path length is higher.

Table 2. Case 2 – Small-world random *directed* graph

Nodes	20	**Has cycles**	Yes
Connections	80	**Rooted spanning tree**	No
Weak connected subgraphs	1	**Minimum In-Degree**	2
Strong connected subgraphs	1	**Maximum In-Degree**	5
Average clustering coefficient	0.3367	**Minimum Out-Degree**	2
Average degree	4	**Maximum Out-Degree**	5
Graph is balanced	Yes	**Average path length**	2.4579

The degree distribution of the directed graph is shown in Figure 6. Handling the directed graph situation, one should account for the number of both the edges leaving a vertice (out-degree) and the ones pointing towards one (in-degree). In this case the curve is similar for both the in- and out-degrees of the graph vertices. The curve shows a peak of 0.65 at the average value of four.

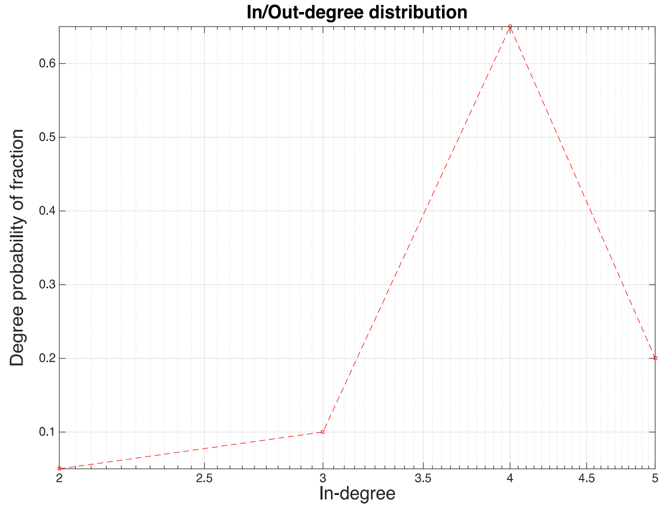

Fig. 6. In-out degree distribution of the directed graph.

Figure 7 illustrates the main results for case 2, modelling of the small-world random directed graph network topology. As anticipated, as the graph is balanced, consensus is achieved in a finite number of iterations. It can be seen more clear how the convergence rates toward consensus vary among individual nodes, based on their place and graph connectivity. Also, the convergence time is considerably higher at 35 seconds, compared to the first case.

Such models can be enhanced by dynamically updating the adjacency and Laplace matrices to account for time-variant topologies. In such situations consensus can be delayed or even fail given reduced connectivity or even partitioning of the network graph on longer spans of discrete time intervals.

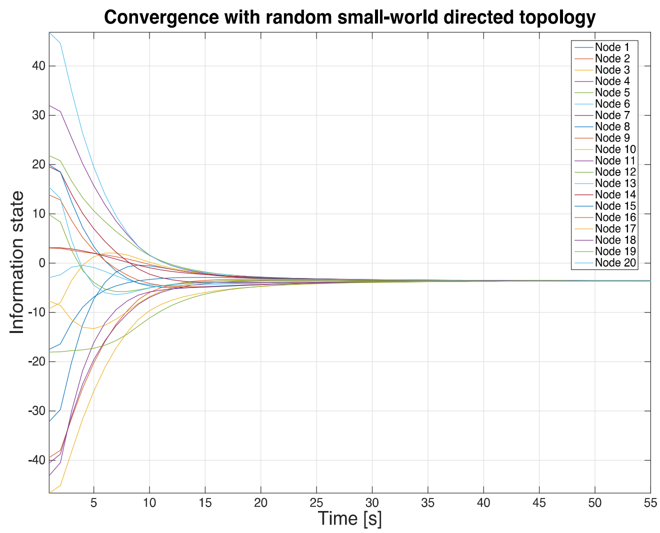

Fig. 7. Convergence analysis for case 2.

4.2 D-LMS consensus with mobility models

The focus is on extending the consensus analysis by the D-LMS algorithm as described by (Mateos et al., 2009) and (Schizas et al., 2009). Based on initial assumptions regarding node location, mobility model and radio channel dynamic performance, consensus is evaluated for both convergence and performance. The algorithm is described by the following recursion for all sensors and bridges:

$$v_j^b(t) = v_j^b(t-1) + c\left(s_j(t) - \left(\bar{s}_b(t) + \eta_j^b(t)\right)\right)$$

$$s_j(t+1) = s_j(t) + \mu[2h_j(t+1)e_j(t+1) - \sum_{b \in \mathcal{B}_j} (v_j^b(t) + c(s_j(t) - \left(\bar{s}_b(t) - \eta_j^b(t)\right)))]$$

$$\bar{s}_b(t+1) = \sum_{j \in \mathcal{N}_b} \frac{c^{-1}v_j^b(t) + s_j(t+1) + \bar{\eta}_b^j(t+1)}{|\mathcal{N}_b|} \quad (9)$$

where $\mu > 0$ is a constant step-size and $c > 0$ is a penalty coefficient. At each time instant, each sensor receives noise affected consensus variables $\bar{s}_b(t) + \eta_j^b(t)$ from the bridge neighbors. It updates its Lagrange multipliers $v_j^b(t)$ and computes its local consensus value $s_j(t+1)$, transmitting $c^{-1}v_j^b(t) + s_j(t+1)$ towards all visible bridges. The iterations is complete when, by acquiring and computing the average of the vectors $c^{-1}v_j^b(t) + s_j(t+1) + \bar{\eta}_b^j(t+1)$, the bridges yield $\bar{s}_b(t+1)$.

A fourteen node network is similarly defined where four of the nodes play the role of bridges – cluster heads. Initial parameters are considered to be the number and positions of all the nodes and the dimension of the deployment area. The model of the communication channel is a logistic function of the distance between neighbours.

$$S(d) = \frac{1}{1+e^{-t}} \quad (10)$$

Figure 8 illustrates the main simulation result in the form of the consensus outcome by plotting the average MSE value across all iterations. In this case the stop condition for the iterations can be set by thresholding the MSE below a certain value, dependant on application requirements.

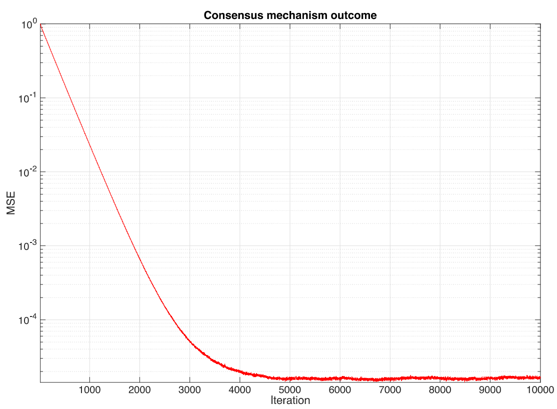

Fig. 8. D-LMS consensus outcome.

5. CONCLUSIONS

The paper discussed the state-of-the-art in consensus algorithms applied for data aggregation in large scale monitoring with wireless sensor networks. By modelling the communication topology using dedicated tools, we have carried out convergence analysis for two types of graphs: random undirected graphs and small world random directed graphs. Results have shown the current performance of local average consensus algorithms for medium sized networks. Convergence was defined based on thresholding the global MSE.

The simulation results were enhanced by D-LMS evaluation with mobility for a reference clustered sensor network with nodes and bridges in an optimal manner. This allowed more detailed insight for complex models of mobility and communication, for optimal consensus.

Current and future work includes the evaluation of the consensus-mechanisms on a laboratory test-bed aimed at industrial networked control through wireless sensor and actuator networks. An alternative path consists of designing the bi-directional interface between the sensor network and UAV, communication and data representation, for reliable cooperative operation.

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REFERENCES

Al-Nakhala Noor, Riley Ryan, Elfouly Tarek, Distributed algorithms in wireless sensor networks: An approach for applying binary consensus in a real testbed, Computer Networks, Volume 79, 14 March 2015, Pages 30-38, ISSN 1389-1286.

Avrachenkov, K.; El Chamie, M.; Neglia, G., "A local average consensus algorithm for wireless sensor networks," in *Distributed Computing in Sensor Systems and Workshops (DCOSS), 2011 International Conference on* , vol., no., pp.1-6, 27-29 June 2011.

Abdaoui, A.; Elfouly, T.M., "Distributed binary consensus algorithm in wireless sensor networks with faulty nodes," in *GCC Conference and Exhibition (GCC), 2013 7th IEEE* , vol., no., pp.495-500, 17-20 Nov. 2013.

Abderrazak, A.; El Fouly, T.M., "On the distributed binary consensus algorithm in wireless sensor networks," in *Signal Processing and Communication Systems (ICSPCS), 2013 7th International Conference on* , vol., no., pp.1-9, 16-18 Dec. 2013.

Boyd S., Parikh N., Chu E., Peleato B., and Eckstein J. 2011. Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers. Found. Trends Mach. Learn. 3, 1 (January 2011), 1-122.

Contreras, Rodrigo, Silvia E. Restrepo, and Jorge E. Pezoa Nunez. "Implementing the distributed consensus-based estimation of environmental variables in unattended wireless sensor networks." *SPIE Security+ Defence*. International Society for Optics and Photonics, 2014.

Choi Jinho; Li Shancang; Wang Xinheng; Ha Jeongseok, "A general distributed consensus algorithm for wireless sensor networks," in *Wireless Advanced (WiAd), 2012* , vol., no., pp.16-21, 25-27 June 2012.

Deroo, F. & Hirche, S. (2013). A MATLAB Toolbox for Large-Scale Networked Systems. at -

Automatisierungstechnik Methoden und Anwendungen der Steuerungs-, Regelungs- und Informationstechnik, 61(7), pp. 506-514.

Elbhiri, B.; Pages-Zamora, A.; Aboutajdine, D., "Real deployment of consensus algorithm on self-organized wireless sensor networks," in *Telecommunications, 2009. ICT '09. International Conference on* , vol., no., pp.119-124, 25-27 May 2009.

Gupta, S.K.; Kar, K.; Mishra, S.; Wen, J.T., "Collaborative Energy and Thermal Comfort Management Through Distributed Consensus Algorithms," in *Automation Science and Engineering, IEEE Transactions on* , vol.12, no.4, pp.1285-1296, Oct. 2015

Jaimes B, A.S.; Jamshidi, M., "Consensus-based and network control of UAVs," in *System of Systems Engineering (SoSE), 2010 5th International Conference on* , vol., no., pp.1-6, 22-24 June 2010.

Jin, Z., & Murray, R. M. (2006). Multi-hop relay algorithms for fast consensus seeking. In IEEE conference on decision and control (pp. 1001–1006), San Diego.

Kar, S.; Moura, J.M.F., "Distributed Consensus Algorithms in Sensor Networks With Imperfect Communication: Link Failures and Channel Noise," in *Signal Processing, IEEE Transactions on* , vol.57, no.1, pp.355-369, Jan. 2009.

Kenyeres, Jozef; Kenyeres, Martin; Rupp, Markus; Farkas, Peter, "WSN Implementation of the Average Consensus Algorithm," in *Wireless Conference 2011 - Sustainable Wireless Technologies (European Wireless), 11th European* , vol., no., pp.1-8, 27-29 April 2011.

Li Yanwei, Zhou Zhenyu, and Sato Takuro, "A Cluster-Based Consensus Algorithm in a Wireless Sensor Network," *International Journal of Distributed Sensor Networks*, vol. 2013, Article ID 547124, 14 pages, 2013.

Lin Xiao, Stephen Boyd, and Sanjay Lall. 2005. A scheme for robust distributed sensor fusion based on average consensus. In *Proceedings of the 4th international symposium on Information processing in sensor networks* (IPSN '05). IEEE Press, Piscataway, NJ, USA.

Loscrí Valeria, Natalizio Enrico, Guerriero Francesca, and Aloi Gianluca. 2012. Particle swarm optimization schemes based on consensus for wireless sensor networks. In *Proceedings of the 7th ACM workshop on Performance monitoring and measurement of heterogeneous wireless and wired networks* (PM2HW2N '12). ACM, New York, NY, USA, 77-84.

Mahmood Muhammad Adeel, Seah Winston K.G., Welch Ian, Reliability in wireless sensor networks: A survey and challenges ahead, Computer Networks, Volume 79, 14 March 2015, Pages 166-187, ISSN 1389-1286.

Mateos, G.; Schizas, I.D.; Giannakis, G.B., Closed-Form MSE Performance of the Distributed LMS Algorithm, in Digital Signal Processing Workshop and 5th IEEE Signal Processing Education Workshop, 2009. DSP/SPE 2009. IEEE 13th , vol., no., pp.66-71, 4-7 Jan. 2009.

Manfredi Sabato, Design of a multi-hop dynamic consensus algorithm over wireless sensor networks, Control Engineering Practice, Volume 21, Issue 4, April 2013, Pages 381-394, ISSN 0967-0661.

Moreau, L., "Stability of continuous-time distributed consensus algorithms," in *Decision and Control, 2004. CDC. 43rd IEEE Conference on* , vol.4, no., pp.3998-4003 Vol.4, 14-17 Dec. 2004.

Moreau, L., "Stability of multiagent systems with time-dependent communication links," in *Automatic Control, IEEE Transactions on* , vol.50, no.2, pp.169-182, Feb. 2005.

Saed, Steve; Lingxi Li; Kim, Dongsoo S., "Decentralized average consensus in wireless sensor networks with probabilistic network links," in *Vehicular Electronics and Safety (ICVES), 2010 IEEE International Conference on* , vol., no., pp.89-94, 15-17 July 2010.

Savic, Vladimir, Henk Wymeersch, and Santiago Zazo. "Belief consensus algorithms for fast distributed target tracking in wireless sensor networks." *Signal Processing* 95 (2014): 149-160.

Schizas, I.D.; Mateos, G.; Giannakis*, G.B*., Distributed LMS for Consensus-Based In-Network Adaptive Processing, in Signal Processing, IEEE Transactions on , vol.57, no.6, pp.2365-2382, June 2009.

Stamatescu G., Popescu D., Dobrescu R., Cognitive Radio as Solution for Ground-Aerial Surveillance through WSN and UAV Infrastructure, Proc. of the 6th Electronics, Computers and Artificial Intelligence Conference, IWSSS Workshop, 23-25 October, Bucharest, Romania.

Stamatescu G., Popescu D., Mateescu C., "Dynamic Task Planning of Aerial Robotic Platforms for Ground Sensor Data Collection and Processing,", Adv. in Robot Design and Intelligent Control, Proc. of the 24th Intl. Conf. RAAD, pp.397-405, Springer, 2015.

Wei Ren; Beard, R.W., "Consensus seeking in multiagent systems under dynamically changing interaction topologies," in *Automatic Control, IEEE Transactions*, vol.50, no.5, pp.655-661, May 2005.