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MODELING AND EVALUATION OF CLUSTERING ALGORITHM PERFORMANCES IN WIRELESS SENSOR NETWORKS USING THE EXPERIMENT DESIGN STRATEGY

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ABSTRACT

In wireless sensor networks (WSN) enhancing the energy efficiency is a major challenge due to the scarce energy resources in sensor nodes. Therefore, many procedures have been developed for maximizing nodes lifespan and reducing the energy consumption without any alteration of sensor features. In this context, we have adopted clustering techniques and a surface experiment design (SED) strategy to optimize some performances in WSN and manage energy reserves. The criteria evaluated are the number of created clusters, connectivity and latency, in function of three significant factors such as the number of system nodes, transmission range and the clusters' size threshold. Through the Taylor-Mac Laurin polynomial equation, we have studied how these factors, their interactions and their quadratic effects can exactly modify the response of the three parameters. So, in order to measure the response of the different parameters, we have employed a clustering algorithm which has been used for efficient energy saving in Wireless Sensor Networks [1]. In addition, a graphical method has been used to carry out the multi-objective optimization of three parameters.

Keywords: surface experiment design, wireless sensor network, clustering, connectivity, latency, multi-objective optimization.

INTRODUCTION

In our world, everything becomes under control through small devices called sensors. Deployed and interconnected to each other via wireless network system, can transmit useful measurement information and control instructions. Thus, the entire physical infrastructure is closely coupled with information and communication technologies. Practically, WSN can be described as a network of nodes that cooperatively sense and control the environment, enabling interaction between control entities and the surrounding environment [2].

Owing to the advances and growth in Micro-Electro-Mechanical System (MEMS) and wireless communication technologies, wireless sensor networks are becoming increasingly attractive for numerous application areas, such as military reconnaissance, disaster management, security surveillance, habitat monitoring, health care, industrial automation, and much more [3]. The sensor node is one of the main parts of a WSN, its hardware consists of: the power and power management module, a sensor, a microcontroller, and a wireless transceiver. The power module offers the reliable power needed for the system. A sensor is in charge of collecting and transforming the signals, such as light, vibration and chemical signals, into electrical signals and then transferring them to the microcontroller. The microcontroller receives the data from the sensor and processes the data accordingly. The Wireless Transceiver then transfers the data, so that the physical realization of communication can be achieved.

A lot of tasks, including information sensing, processing and transmitting are operated with limited power. Since batteries in sensors have finite stored energy and it is generally not convenient to replace or recharge these batteries, a critical issue in WSNs is to achieve high energy efficiency in order to prolong the network lifetime.

The remaining parts of this paper are organized as follows: The section 2 gives a short overview of some clustering algorithms proposed in the literature and introduces the surface experiment design. Then, the section 3 explains the mathematical simulation of processes and results. After that, modeling and evaluation of the used clustering algorithm performances (latency, number of created clusters and connectivity) are discussed in sections 4, while the multi-objective optimization of the three parameters together is presented in section 5. Finally, section 6 concludes this paper.

RELATED WORK

The recent investigation tendency in WSNs is focused on energy optimization with the challenge: increasing sensor lifespan. Clustering is one of the essential energy efficiency operations performed to prolong network lifetime [4]. A clustered WSN is typically consisted of a base station (BS) and a certain number of clusters. Each cluster in turn is composed of a cluster head (CH) and some non-cluster head (NCHs) nodes. So, the CH is responsible for receiving data from the NCHs, processing the data and then forwarding the information to the BS, either directly or via one or multiple relay nodes [5, 6]. The relay nodes are responsible for forwarding data received from other nodes and may not necessarily be responsible for local sensing. In clustered WSNs, transmitting to a nearby CH rather than a possibly far away BS helps to reduce the energy consumption of the NCHs. However, CHs may be heavily burdened since they need to process and transmit the data for the whole cluster. This may shorten the lifespan of the CHs, especially in the absence of the relay nodes between the CHs and the BS. Lowering the energy consumption of the CHs therefore usually plays a critical role in prolonging the lifetime of the clustered WSNs. Since the communication distance

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largely determines the energy consumption of data transmission, finding a good location for each CH is of critical importance for prolonging network lifetime: an inappropriate CH location may force the CH node to communicate with the BS over a long distance and consequently uses up its stored energy quickly.

Several clustering algorithms have been developed as approach to resolve the problem of energy in WSNs [4]. The popular one is LEACH [7] for low-energy adaptive clustering hierarchy which is introduced as hierarchical routing protocol to reduce energy consumption by aggregating data and transmitting it to the sink via CHs. By this algorithm we space out lifespan of nodes by doing only the minimum work it needs to transmit data [8]. Indeed, LEACH algorithm can reduce energy consumption 7 times compared with direct communication and between 4 to 8 times compared with minimum transmission energy (MTE) routing protocol [9]. Due to its drawbacks [10], many variant protocols based on LEACH protocol are introduced in order to improve it [11], for instance: M-LEACH [12], C-LEACH [13], TL-LEACH [14], V-LEACH [15] and K-LEACH [16].

Another effective algorithm as distributed clustering approach for long-lived ad-hoc sensor networks is HEED for Hybrid Energy-Efficient Distributed clustering [17, 18]. It periodically selects cluster heads according to a hybrid of the node residual energy and a secondary parameter, such as node proximity to its neighbors or node degree. HEED can asymptotically guarantee connectivity of clustered networks, space network lifetime and support scalable data aggregation.

PEGASIS for Power-Efficient Gathering in Sensor Information Systems [19], is an improvement over LEACH since each node have been able to communicate only with a close neighbor and take turns transmitting to the base station, avoiding the formation of clusters. Thus reducing the amount of energy spent per round. Nevertheless, PEGASSIS is more specific for wireless sensor where nodes are immobile, its performances decrease in a case of mobile environment.

The protocols cited above have been simulated in order to show their performances. In PEGASIS, the metric simulated is the system lifetime in function of the round number, whereas in HEED, the number of iterations is evaluated. Similarly in LEACH, the metrics simulated are “energy dissipation” and “system lifetime” in function of network diameters and round numbers respectively. Eventually, these simulations have shown how powerful the algorithm is, in terms of reducing energy and extending the network lifespan.

In WSNs, performances are evaluated using several simulation tools, and most of them are carried out with a classical approach by varying only one factor at a time. However, the design of experiment (DOE) strategy [20] can manipulate multiple inputs at the same time and identify important interactions that may be missed in classical simulation. In addition, all possible combinations can be investigated with limited runs, confirming suspected input/output relationships in a predicted equation. Thus, using DOE is a powerful tool in a variety of experimental situations. The major types of designed experiments as described in [20, 21] are: (i) full and fractional factorials; (ii) response surface analysis; and (iii) mixture experiments.

In full factorials, we study all of possible treatment combinations that are associated with the factors and their levels. They look at the effects that the main factors and all the interactions between factors have on the measured responses. However, with response surface analysis, which is an off-line optimization technique, we run a series of full factorial experiments and map the response to generate mathematical equations that describe how factors affect the response. Finally, we can run the mixture experiments when the factors of process are components of mixture under constraints or not.

In this paper we have implemented the central composite design as a response surface methodology to estimate, in a second-degree polynomial model, the variability of some WSN performances to some most fluently explanatory variables. We have evaluated the number of created clusters, connectivity and latency in function of the number of system nodes, transmission range and the threshold of cluster size. Firstly, we discuss separately the effect of three factors on response variables. Secondly, we perform the multi-objective optimization of the three parameters together in order to draw the compromise of responses as much as possible. We have simulated the DECHP protocol for Distributed Energy-efficient Clustering Hierarchy Protocol as an algorithm to calculate the three responses (more details in [1, 6]).

PROCEEDING AND RESULTS

Surface experiment design model

The mathematical strategy used is a design of experiment which links, in a polynomial model, the response and factors that can modify it. We have modelled three parameters such as latency, the number of created clusters and connectivity, in function of three variables seemed having effects on the variation of the three responses. We have chosen a quadratic polynomial model which in coded variables takes the following form: (e_1): $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{23} X_2 X_3$

In matrix form: $Y = \beta X + \varepsilon$ and that involves $\beta = (X'X)^{-1} X'Y$

While ε is an experimental error and β, which are determined by a least square criteria [21], are the coefficients of the model.

The experiments have been carried out by using the rotatable central composite-uniform design with five levels for each factor, and coded by: *–1, 6817; –1; 0; +1* and *+1, 6817*. The three factors and their variation margins are grouped in Table-1. The required number of experimental points is 20.

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Table-1. Real and coded values of three parameters for design of experiments.

Symbol	Factors/Levels	Lowest	Low	Centre	High	Highest
	Coded variables	-1,6817	-1	0	+1	1,6817
X_1 = Nn	Number of nodes	1	21	50	79	99
X_2 = txRang	Transmission range	1,47759	10	22.5	35	43,5224
$X_3 = \chi$	Cluster size threshold	4,9546	7	10	13	15,0453

DECHP clustering algorithm

To calculate the three responses, we have carried out the execution of DECHP algorithm [1] using MATLAB software as simulator. The DECHP which is based on routing protocol, utilizes a fully distributed approach to set up clusters and routing paths, performs rotation of cluster heads (CH), and carries out other energy intensives tasks. The proposed algorithm partitions the network into different clusters based on:

- The cluster size (number of sensors): this equilibrates the clusters in terms of sensors nodes present in the cluster by defining a threshold "χ" of sensor nodes that a cluster can regroup (depending on CH capacity to handle traffics).
- The distance between the nodes constituting the cluster: this allows an improvement of intra-cluster communication quality by reducing the interferences, wireless fading as well as the energy consumption.
- The energy level of each node: this leverages the network lifetime by balancing the energy capacity all over the clusters.

After the creation of the clusters, a CH is elected from each cluster. Then, CHs use a geographical and energy aware neighbor CHs selection to join the base station (BS). All non-cluster head nodes transmit their data to the CH, while the CH node receives data from all the cluster members, performs signal processing functions on the data (data aggregation) and transmits result data to its upper level CH and so on till the data reaches the BS. However, since the CH is limited by the energy, a reconfiguration procedure is usually required in wireless sensor networks. Unlike the other existing clustering schemes where the CH reconfiguration is invoked periodically resulting in high communication overhead, DECHP is adaptively invoked to change only the CHs by taking into account their remained energy levels. That is, the cluster creation is made only at the system activation, afterwards only the CHs are changed.

The algorithm has the following form:

(e2): $$W_{EC} = \alpha\left\| EC \right| - \chi\right| + \frac{2\beta}{\left(\left|EC\right|^2 - \left|EC\right|\right)} \sum_{j,k \in EC} d(j,k) + \gamma \sum_{j \in EC} \frac{1}{C_e(j)}$$

Where α, β and γ are weights which are relied by fundamental equation of mixture α+β+γ= 1. In order to offer the equality in chance for the dominance of three factors, we have assigned the rate 1/3 for each one. While |EC| is the size of equivalence class EC; χ is the predefined threshold which limits the number of nodes that are controlled and managed by cluster dead; d(j,k) is a distance between two nodes j and k; and $C_e(j)$ is the current energy level of node j.

The three metrics evaluated as performance of DECHP scheme are: *(i)* the number of created clusters; *(ii)* the connectivity; and *(iii)* the latency. The connectivity is defined as the probability that a node is reachable from any other node, whereas the latency represents the delay incurred by the nodes in the same cluster to obtain their shared resource (as in TDMA). These three parameters are studied by varying number of nodes in the system Nn, transmission range txRang, and cluster size threshold χ, which represents the number of nodes that each cluster head can handle in terms of resource allocation. On the one hand, a small value of χ leads to partition the network with small clusters' size, which is inefficient as the use of resources at the nodes is wasted. On the other hand, large value of χ leads to partition the network with large clusters' size, which in turn increase the overheads, and the system efficiency suffers in the sense that the nodes will incur more delay (in TDMA) to get their shared resources.

The operatory conditions and results of the DECHP algorithm simulation for the number of created clusters and latency performances are regrouped in Table-2.

Table-2. Results of created clusters' number and latency performances using the rotatable central composite-uniform design of experiments.

Runs	Nn	txRang	χ	Number of created clusters	Latency
1	21	10	7	21	0,1
2	21	10	13	21	0,1
3	21	35	7	11	0,190909091
4	21	35	13	11	0,190909091
5	79	10	7	79	0,1
6	79	10	13	79	0,1
7	79	35	7	15	0,526666667
8	79	35	13	16	0,49375
9	1	22,5	10	1	0,1
10	99	22,5	10	16	0,61875
11	50	1,47759	10	50	0,1
12	50	43,52241	10	14	0,357142857
13	50	22,5	4,954622	16	0,3125
14	50	22,5	15,04538	16	0,3125
15	50	22,5	10	16	0,3125
16	50	22,5	10	16	0,3125
17	50	22,5	10	16	0,3125
18	50	22,5	10	16	0,3125
19	50	22,5	10	16	0,3125
20	50	22,5	10	16	0,3125

MODELING AND EVALUATION OF DECHP PERFORMANCES

Latency

In Wireless sensor networks, a low latency is needed when transmitting data from node to node or to other devices as part of the network. The nodes should start its activity when receiving their proper signals and transmit gathered data, relatively in a short period of time. Eventually, the network preserves its quality of service by doing control and communication between its components in desired time.

Basing on modeling approach, we have evaluated the effect of the number of nodes, the transmission range and the size threshold of created clusters on latency in WSN. The statistical treatment of response "latency" using Enova approach [21] has provided the influence degree of each factor, and confirmed the validation of our choice with a limited significant threshold.

The regression of latency is significant with a confidence level of 99.9%. Indeed, the Fisher-Snedecor experimental factor "F_{exp}" is higher than the critical one F_{cr} (F_{exp} = 10, 1366 > $F_{cr0.001}$ (9, 10) =10.044). That explains the strongest relation between latency and factors, which means that the variation of latency is involved by the variation of different factors. In addition, the regression correlation coefficients R^2 and $R^2_{adjusted}$ present good values 0.90 and 0.81 respectively. Hence, this leads to carry out all possible statistical treatments with interpretations and determine the coefficients of the model.

With a significant threshold of 2.5%, that is to say with a confidence interval of 97.5%, the variation of latency is very closely dependent on the variation of variables such as: the number of nodes Nn, the transmission range txRang, the two-degree interaction between the number of nodes and the transmission range Nn-txRang, and then the square degree of the transmission range $txRang^2$. Hence, those variables affect latency and are significant for the mathematical model. However, the other variables such as: the threshold of created clusters' size χ, the interactions txRang-χ and Nn-χ, and the squares of number of nodes Nn^2 and then χ^2 do not significantly affect latency.

The effect curves of different factors (Figure-1) show that the number of nodes presents a positive influence on latency which increases when number of nodes increases. Analogously, for the transmission range txRang which affects positively the latency. So, the very lower values of latency are obtained for small quantities of both variables, while the threshold of created clusters' size is not significant.

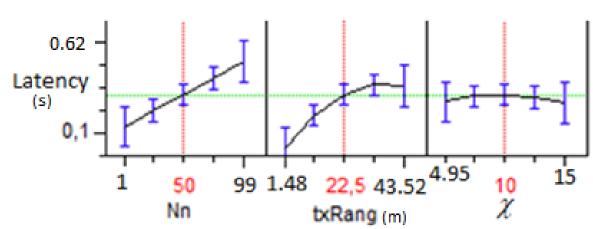

Figure-1. The effect curves of three factors: Nn, txRang and χ on latency.

VOL. 12, NO. 15, AUGUST 2017 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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In addition, the second degree interaction Nn-txRang (Figure-2) affects positively the latency. So, the lowest values of latency are referred to the lowest levels of Nn and txRang when they are jointly taken. However, the effect of $txRang^2$ (equation e_2) on latency is negative and presents a weak influence. This weakness is dominated conjointly by the coexistence of factors such as the number of nodes Nn, the transmission range txRang and the interaction Nn-txRang. The three factors together present an influence weight of 81.43% against 12.23% for the square of transmission range $txRang^2$.

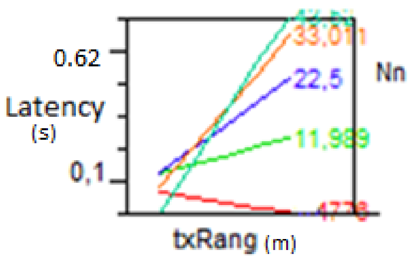

Figure-2. The effect curves of the interaction Nn-txRang on latency.

The mathematical model is a powerful tool to predict the optimal response for any input parameter values inside the experimental domain. So, basing on experimental plan we have obtained the second order polynomial model by applying multiple regression analysis. In coded variables the equation (e_2) takes the following expression:

(e_2) : $Y\ (latency) = 0.315 + 0.111\ X_1 + 0.105\ X_2 - 0.002\ X_3 + 0.001\ X_1^2 - 0.046\ X_2^2 - 0.016\ X_3^2 + 0.080 X_1X_2 - 0.004\ X_1X_3 - 0.004\ X_2X_3$

where X_1, X_2 and X_3 represent respectively Nn, TxRang and χ.

Eventually with a confidence level of 97.5% the (e_2) can be reduced to the following form:

(e_3): $Y\ (latency) = 0.315 + 0.111\ X_1 + 0.105\ X_2 - 0.046\ X_2^2 - 0.016\ X_3^2 + 0.080\ X_1X_2$.

The term X_3^2 is not significant but is added to the model in order to improve the quality and preserve the good characteristics that the model should have (e_3: R^2=0.90). So, by transforming the coded polynomial model (e_3) into polynomial model consisted of real variables, we have obtained contour plots Figure-3 as isoresponse curves (we have adopted the same procedure for the other presentations). Indeed, they relate the variation of latency on number of nodes Nn and the transmission range txRang while the size threshold of created clusters, which has no effect on latency, is taken at any desired level (e.g. X_3=0). By this strategy we can draw the interest zones in term of desired latency and yield predictive results quickly. For instance, along the contour 0.3 of latency we have obtained many possibilities and choices for the couple (txRang, Nn). Then, the representation in 3D of figure 4 shows clearly the zones of interest in term of latency in function of Nn and txRang.

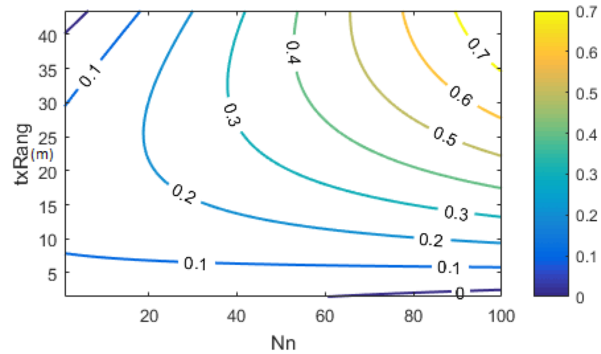

Figure-3. Isoresponse curves of latency in function of Nn and txRang.

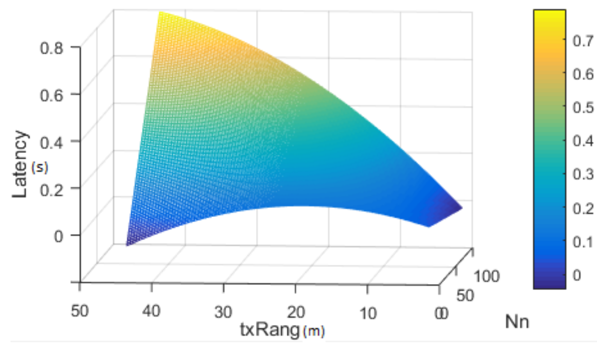

Figure-4. The variation in 3D of latency on (Nn, txRang) plan.

Number of created clusters

The analysis of variance and the multiple regression analysis indicate that the regression "number of created clusters" in function of the three factors is significant with a threshold of 99%. As a result, it has good statistical characteristics which lead to determine and make interpretations of the regression model.

The results show that the number of created cluster is mostly depended on the variation of Nn, txRang, $txRang^2$ and the two-order interaction Nn-txRang. Those factors affect significantly the response number of created clusters with a confidence interval of 97.5%. Under this value, the other remaining factors such as χ, Nn^2, χ^2, Nn-χ and the interaction txRang-χ are not significant, they have weak statistical features, so they are excluded from the global polynomial model. So, in coded variables, the polynomial model is written as the following form:

(e4): $Y = 15.59 + 11X_1 - 15.2\ X_2 + 0.07\ X_3 + 0.011\ X_1^2 + 8.32\ X_2^2 + 2.66\ X_3^2 - 13.37\ X_1X_2 + 0.125\ X_1X_3 + 0.125\ X_2X_3$

The equation above *(e4)* is reduced, with a confidence interval limit of 97.5% and a significant threshold of 0.025, in the following form (e5):

(e5): $Y = 15.59 + 11\ X_1 - 15.2\ X_2 - 13.37\ X_1X_2 + 8.32\ X_2^2$

The effect curves of three factors (figure 5) show that the response "number of created clusters" increases when Nn increases and vice-versa. Indeed, this factor affect positively (e5) the number of created clusters.

VOL. 12, NO. 15, AUGUST 2017 ISSN 1819-6608
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However, the txRang affect negatively the response number of created clusters. That means the higher txRang is the fewer number of clusters will be created. Furthermore, the interaction Nn-txRang (Figure-6) affects negatively the response which takes a high value when Nn and txRang are conjointly at the low level.

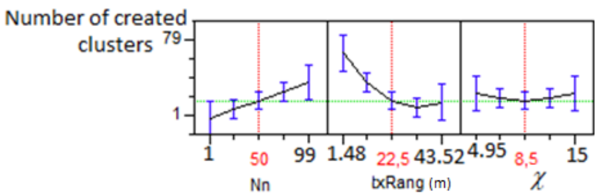

Figure-5. The effect curves of three factors: Nn, txRang and χ on the number of created clusters.

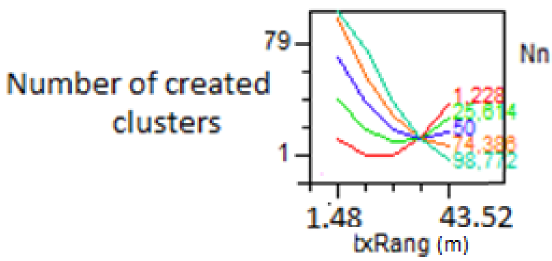

Figure-6. The effect curves of the interaction Nn-txRang on the number of created clusters.

In order to increase the number of created clusters, the number of nodes should be at the higher level while the transmission rang at the lower. Nevertheless, the strongest effect is related to the negative effect of txRang and the interaction Nn-txRang against the effect of Nn. Indeed, the effect of (txRang + Nn-txRang)/the effect of Nn is equal to 56.14/21.62 = 2.58. Eventually the square of txRang affects positively the response "number of created clusters" with a weight of 16.35%, which increases roughly when txRang increase by the power of its square degree.

In Figure-7 the interest zones of curves, which represent the variation of the created clusters' number in function of Nn and txRang, are designed. It gives more possibilities in choices of the couple (Nn, txRang). While in Figure-8 the isosurface curves in 3D are represented showing how the number of created clusters is when both Nn and txRang vary collectively.

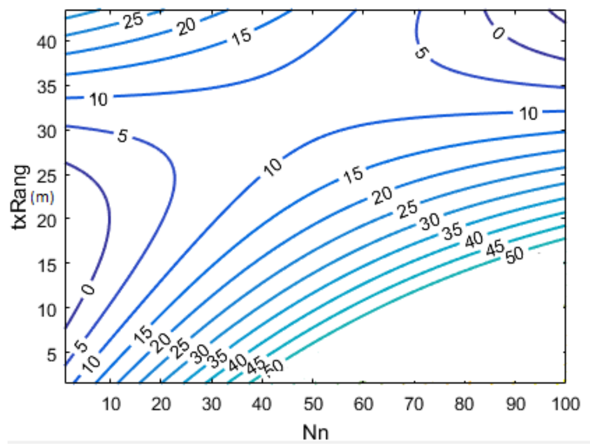

Figure-7. Isoresponse curves of the created clusters' number in function of Nn and txRang.

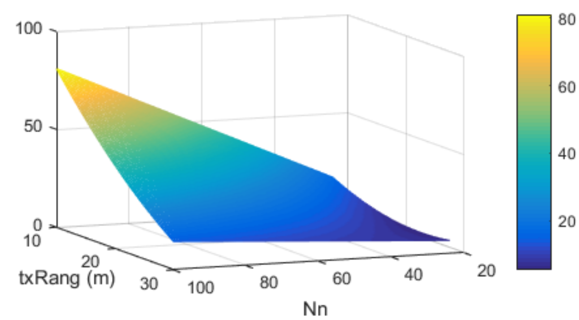

Figure-8. The variation in 3D of the created clusters' number in the (Nn, txRang) plan.

Connectivity

While the modeling approach used for the study of latency and the number of created clusters has their features and merits, it has some limitations in case of connectivity. Indeed, the statistical model obtained doesn't represent perfectly the response connectivity, and some of constraints still not verified by applying the rotatable central composite design. Hence we have alternatively adopted Box-Behncken design [20] as a surface design to evaluate statistically the regression of connectivity in function of three variables Nn, txRang and χ. In total, we have provided 15 runs instead of 20. Twelve different combinations are made with the lowest, highest and medium levels of three factors and the 3 remained are carried out at the center of the experimental domain. The lowest limit of nodes number is determined according to the highest level of the transmission range that preserves connectivity in the entire network. So, we have chosen the variation margins of three factors with the limits below: $24 \leq Nn \leq 100$, $10 \leq txRang \leq 30$ and $4 \leq \chi \leq 20$.

The analysis of variance and the multiple regression analysis indicate that the Fisher's experimental factor (Fexp=6.62) is higher than the critical one ($F_{0,01}(9, 10) = 4.94$) with a significant threshold of 1%. Thus the regression is significant and the variation in response "connectivity" is due to the variation of factors.

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The most significant factors on connectivity are the Nn, txRang and the square of χ "χ^2" which respectively present Fisher's experimental factors of 21.33, 22.09 and 10.19 superior than the critical one ($F_{0.025}(1,10)$= 6.94) with a confidence interval of 97.5%. More specifically the transmission range txRand affects positively the connectivity which increases when txRang increase (Figure-9), and the same effect is yielded when the number of nodes increases, while the square of the threshold χ affects negatively the response "connectivity". In the experiment design strategy, for improving the quality of the regression and extending its study, it is convenient to add some factors to the mathematical model even though didn't affect significantly the connectivity. So, with negative effects, the factors Nn^2, $txRang^2$ and Nn-txRang are added with their effect weights respectively 7.4%, 8% and 15.2%, so the final regression (e6) which presents a good statistical criteria (R^2= 0.92) is modeled as follow:

(e6) : $Y(connectivity) = 1 + 0,359\ X_1 + 0,369\ X_2 - 0,113\ X_1^2 - 0,126\ X_2^2 - 0,366\ X_3^2 - 0,239\ X_1X_2$

The variation of connectivity in function of χ admits a maxima when χ takes the medium level i.e. X_3=0 (χ=12 in real variable). We have chosen this value as an appropriate level to study the connectivity on plan (Nn, txRang) considering that χ has no significant effect on it.

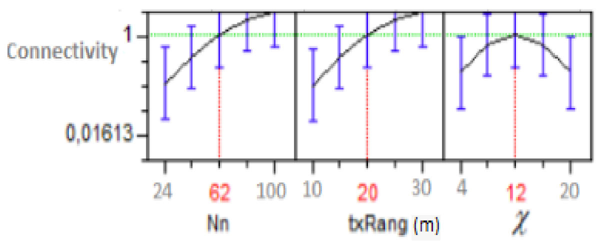

Figure-9. The effect curves of three factors: Nn, txRang and χ on connectivity.

Basing on the polynomial model (e6), we have drawn in figure 10 the contour plots in term of connectivity on the plan (Nn, txRang) while X_3 is taken at the center of its variation domain (X_3=0). On the explored domain defined by the plan (Nn, txRan), the network stills connected in the zone where Y(connectivity) is higher than one (colored area). In this zone, the connectivity of the network is insured, and is limited by the curve of the function defined by (e7). Along this curve the connectivity equals to 1 and is considered as the border of the connected zone in the entire network referring to the plan (Nn, txRang). Finally, in the Figure-11 is shown the representation in 3D of the connectivity on the plan (Nn, txRang).

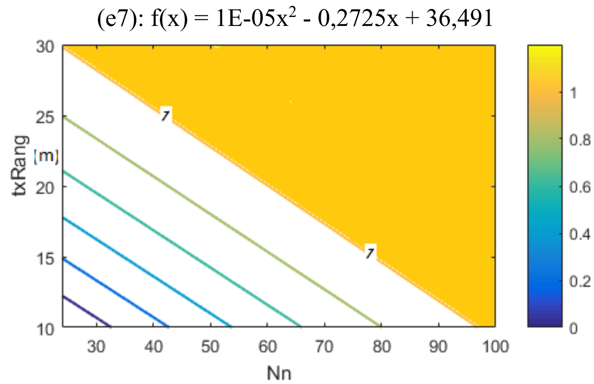

Figure-10. Isoresponse curves of the connectivity in function of Nn and txRang.

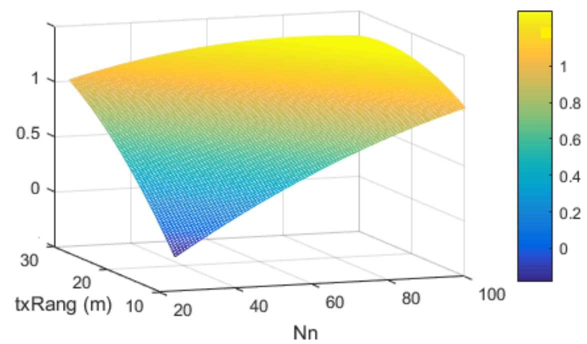

Figure-11. The variation in 3D of the connectivity in the (Nn, txRang) plan.

MULTI-OBJECTIVE OPTIMIZATIONS

The multi-objective optimization is consisted in research as the compromise area in which the three metrics are together verified. Indeed, this is obtained by superimposition of their objective contour plots. Furthermore, forbidden regions where one or more than metric present constraints are excluded from the study. The Figure-12 shows the superimposition of contour plots for the three performances on the plan (Nn, txRang) where specifications are respected for latency, the number of created clusters and connectivity together. The specified margin for Nn and txRang is provided according to the connectivity study. So, the number of nodes is evaluated between 24 and 100, and txRang varies from 10 to 30 m while the threshold size of created clusters is taken at the center of its variation domain because of its weak influence. We have extracted, from the colored area, some compromise and optimal zones where the connectivity of the network is insured and the other metrics have optimal values (Table-3).

Table-3. Some compromise responses of connectivity, latency and the number of created clusters.

Nn	txRang	Connectivity of network	Latency	Number of created clusters
95	12	100%	0.26	69
95	28	100%	0.58	19
65	20	100%	0.34	26
30	28	100%	0.25	7

Basing on the plots, a very low consumption of energy could be carried out with a low transmission range (e.g txRang=10m) and a very high number of nodes (e.g 95 nodes). With those values the energy dissipated within communication is reduced. Nevertheless, for very low number of nodes we have to increase the transmission range in order to preserve the connectivity of network.

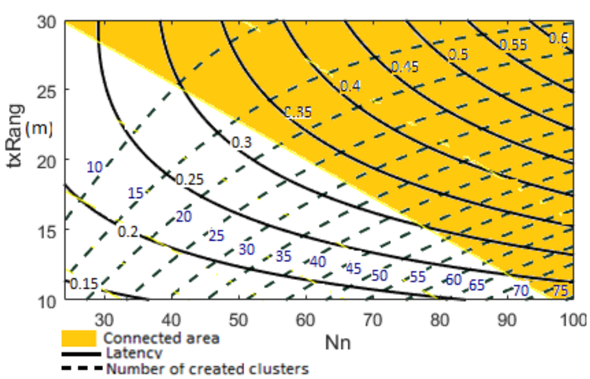

Figure-12. Graphical zones in which specifications are respected for three responses "latency", "connectivity and "the number of created clusters.

CONCLUSIONS

In our study, we have deeply evaluated three performances in WSN namely latency, number of created clusters and connectivity for DECHP algorithm, which has been used for efficient energy saving in Wireless Sensor Networks. We have successfully applied the design of experiment strategy as a tool to evaluate the three performances in function of three parameters such as the number of nodes, the transmission range and the created clusters' size threshold. In addition, we have used the graphical method to carry out the multi-objective optimizations of the three objectives. Finally, through polynomial models obtained we could manage energy resources and extend the network lifetime by controlling the three performances in the compromise area.

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