Dynamic Coalitional Matching Game Approach for Fair and Swift Data-Gathering in Wireless Body Sensor Networks

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***Abstract*—Wireless Sensor Networks are deployed in different fields of application to gather data on the monitored environment. The Wireless Body Sensor Network (WBSN) is a wireless sensor network designed to monitor a human body vital and environment parameters. The design and development of such WBSN systems for health monitoring have been motivated by costly healthcare and propelled by the development of miniature health monitoring devices. This paper presents the architecture design of a preventive health care monitoring system. This architecture is designed for monitoring multiple patients in a hospital. It is based on a set of mobile data collectors and static sensors for analysis of various patient's parameters. The data collectors need to cooperate together in order to gather the data from the sensor nodes. The point of this paper is how to dynamically and effectively appoint and deploy several data collectors in the hospital to gather the measured data in minimal time. We formulate the problem as a coalitional matching game between patients and data collectors, and we propose a patient-data collector association algorithm that ensures fairness and minimum total course in the stable matchings.**

***Keywords*—Coalitional matching game; Distributed machine learning; Stable Matching; Wireless Body Sensor Network; Health monitoring; Behavior derivation and verification.**

I. Introduction

A Wireless Sensor Network (WSN) consists of a number of wireless sensors. The use of WSN has allowed to have great advancements in various aspects of sensing. The advantage of WSNs compared to wired networks is their ease of deployment. The sensors are capable of sensing and processing various conditions at divers locations. The commonly monitored conditions are environmental and human vital functions. The sensors transmit the measured data to a base station which analyzes and reacts according to the observed data in the monitored environment. Many monitoring applications rely on Wireless Sensor Networks, WSNs, have been developed in various fields of application (e.g. military, industrial processes, environment , agriculture and e-health monitoring) to gather data on the monitored environment.

Health care monitoring systems monitor a patient health status. These systems need high performance and low cost solutions to achieve the surveillance operation. The wireless sensor networks are an effective solution to guarantee such requirements in health monitoring systems. Wireless body sensor networks (WBSNs) for health monitoring are able to monitor the people health parameters. They consist of on-body sensors attached to a patient and environmental sensors deployed around the patient. The on-body sensors are used to monitor conditions or parameters such as blood pressure, heart activity, oxygen saturation, etc. While the environmental sensors monitor the ambient parameters in the vicinity of the patient such as room temperature, humidity level, etc. These parameters together constitute a patient health status. They can be consulted by the medical staff without affecting the patient daily activities.

Many applications of Wireless Body Sensor Networks (WBSNs) have been developed to monitor a particular disease or a set of health parameters of the patients at their homes [1]–[3] or in a health center. The works in [4]–[6] provide a continuous health monitoring of patients at their home without restricting their activities and body movements. Wireless sensor networks are also used to perform daily physical activity recognition [7, 8] and for continuous and real-time monitoring of health [9]. The authors of [10] illustrate the design and implementation of an e-health monitoring networked system. The architecture of this system is based on smart devices and wireless sensor networks for real time analysis of various parameters of patients. In [11], a Wireless Sensor Network personal health monitoring system for collection and dissemination of medical sensor data is proposed. It allows data storage correlation and dissemination as well as timely alerts when parameters are breached.

Nevertheless these works use a data collector to gather measured data from the sensors. They are mainly focused on the implementation issues, and they rarely address the design and maintenance of such systems. Furthermore these systems do not address the cooperation between the data collectors in order to achieve their tasks. A WBSN system design should get through a stated methodology to deal with the construction and maintenance of these systems. The architecture design in [12] uses data collector devices that accumulate and process data from on-body and environmental sensors. The collected data is furthermore relayed to a medical center to facilitate accelerated diagnosis of diseases and also increased efficiency and accuracy in the health monitoring process. The authors in [13] propose a model driven (MDE) approach to deal with the design and verification of the WBSN-based preventive health care applications. This approach derives the WBSN components behavior by transforming the WBSN global requirements and verifies whether the derived system behaves correctly according to its global specification, the objective is to increase system performance and QoS.

Therefore, swift deployment, sensing accuracy, low-cost, and reliable delivery are key features to be inspected in WBSN system to perform efficiently its tasks: signal sensing and in-node signal processing to transmit collected data through dedicated wireless transceiver among themselves and with a central controller [14]. However, nowadays applications require more than this [15]. Tracking, monitoring, self-organizing, local information treatment, and autonomy of decision are crucial but very involved characteristics to build dynamic, optimal, and reliable WBSN system. Game theory is particularly a promising and powerful concept to investigate such complex WBSN design [16].

Game theory [17] is a mathematical framework to model and analyze various conflict and cooperation situations between rational agents called players. It allows to describe and study interactive strategic decisions and behavior of the players and yields formal rules for predicting equilibrium and stability solutions [18]. In general, a WBSN system consists of numerous sophisticated and autonomous sensors devoted for a particular job which can interact and exchange information between each others or with a global controller. Hence, for centralized and distributed WBSN systems, to attain a maximal reward, players can either cooperate or compete with each other. The cooperative game or coalitional game theory [19, 20] focuses on: i) the possibility to forge coalitions between players with common interests and incite them through external enforcement to cooperate, ii) how to divide the collective payoffs among the coalition members, and iii) the competition between the different coalition. From this perspective, forming coalitions between WBSN nodes can yield interesting results in battery life extension, data delivery reliability, reducing data gathering delay, tracking and surveillance, [21]. Matching game theory is also a field of cooperative game that deals with the analyze of the formation of relationships between two sets of players with strict preferences: schools/bachelors, firms/employees, marriage, roommates, etc. In this class of game even though the cooperative assumption, due to the rationality condition, the pairwise stable strategy profile must match the profile that maximizes the total outcome.

But the non-cooperative game theory is also of interest, especially to analyze selfish players interaction [22]. Indeed, channel congestion, energy conservation, and interference suppression issues in WBSN can be solved with the help of Nash equilibrium (NE) which is the leader solution concept for non-cooperative games [23, 24]. Each player strategy in the NE profile corresponds to the best response to all other strategies in that equilibrium profile.

Game theory allows mathematical solutions to model and solve scenarios of interdependent decision makers which expects to be complex for a large number of players and with important game rounds. Distributed learning algorithms provides the update instruction that allow the decision maker to compute the optimal strategy in each iteration and then converge, or not, to the equilibrium solution [25].

In this paper, we focus on the design of dynamic data-gathering in WBSN system based on colaitional matching game theory. Our WBSN architecture consists of a set of patients randomly placed in the hospital wards, and a set of nurses equipped with data collectors to periodically gather the measured data from on-body and environmental sensors and transmit it to the medical center. The deployment of these data collectors in the hospital area and their trajectory can be statically defined by the administrator. This strategy can generate fairly large collection times. Hence, we go for distributed solution which yields a formal strategy to achieve dynamic deployment of data collectors to gather measured data in the hospital. This solution may ensure fair workload for all data collectors and aim to identify the minimal course for each data collector in the WBSN. We use coalitional matching game to establish coalitions of patients based on their geographic emplacements in the hospital and then appoint for each coalition the nurse so that their preferences match. The cooperative character of our data-gathering game allows that the overall system performance in terms of total patients coverage, nurse workload fairness and the optimal course to serve patient in each data collect period can be reached in the stable matchings obtained mathematically and under distributed learning algorithm. This distributed course calculation approach is then incorporated into the derived data collector behavior.

The rest of the paper is organized as follows. The design architecture of our WBSN system is presented in Section II. In Section III we present the coalitional matching game for a cooperative data gathering. Section IV presents and discusses the numerical results. Finally, we conclude with a discussion in Section V.

II. WBSN Architecture

We consider a WBSN architecture illustrated in "Fig. 1" to monitor a set of patients $\mathcal{P} = \{p_1, , p_i, , p_N\}$ in a hospital. The

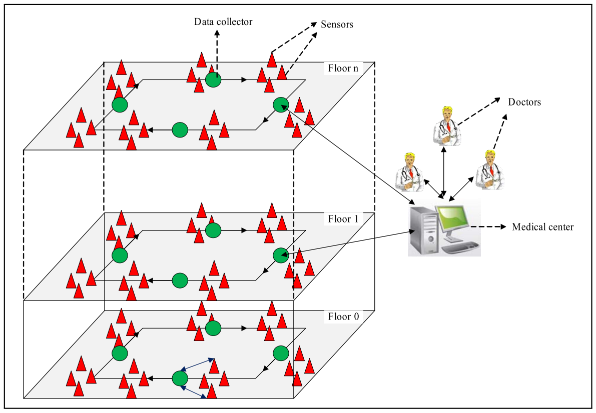

Fig. 1: WBSN for health monitoring architecture

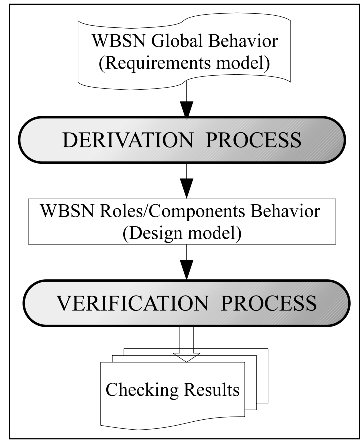

Fig. 2: The Model driven derivation and verification approach

hospital is composed of many floors and each floor consists of a number of patient's rooms. We assume that each room's patient is equipped with sensors to monitor the surrounding of the patient such as gas detection, room's temperature, oxygen level and beyond. The medical sensors are attached to the patient to monitor his vital parameters. They are used to analyze the health of the patient by measuring various vital body parameters such as heart rate, blood pressure and body temperature. These sensors produce values of data which represent together the real time situation of the patient at all times. We consider a set of nurses $\mathcal{N} = \{n_1, \ldots, n_j, \ldots, n_M\}$ equipped with a mobile data collector to periodically gather the measured data from the sensors. Then they convert the collected values into meaningful metadata by adding a unique identifier of patient, type of parameter being monitored, time and unit of measurement to made these values meaningful. The mobile data collector can either consume the collected data for its own purpose (displays the physiological information on a user interface) or transmit it to a medical center. The presence of humans in this process is crucial. It allows analyzing the collected data, notes the patient's status and performs maintenance on the network if necessary (e.g. wrong position of a sensor). The nurse may request assistance directly to other nurses or doctors who are also equipped with a PDA or a smart phone.

To ensure a WBSN system global behavior, we argue that the decomposition on collaborative components should be fruitful. Once the behavior of the system components is obtained, we must ensure that it runs without any errors. For this end, we use the model driven engineering (MDE) approach proposed in [13] to derive the behavior of the WBSN system components and verify the derivation process."Fig. 2" shows an overview of the model driven derivation and verification approach.

We consider nurses and patients mobility; in each data-collect period, the system architecture changes dynamically where some of them were add as well as leave. In our 3D system model, each patient p_i and nurse n_j have a coordinates vectors in a given period $p_i(x_i, y_i, z_i)$ and $n_j(\tilde{x}_j, \tilde{y}_j, \tilde{z}_j)$, respectively. To gather data, the nurses will not perform randomly or statically, but based on the patient location to optimize their course and then minimize their effort. This fact may lead to selfish nurses, who tend to conserve their energy through minimizing the effort to gather data, and decrease the system reliability. To overcome the nurse selfish behavior, we take use of cooperative game theory, especially coalitional matching game, to upgrade our architecture model and reach a total patients coverage, workload fairness and optimal total course.

III. Coalitional Matching Game

To model the system as a coalitional matching game, we consider the two finite and disjoint sets of players: $\mathcal{P}$ of patients equipped with sensors and $\mathcal{N}$ of nurses equipped with data-colectors. We denote this game by $\Gamma = \langle \Pi(\mathcal{P}), \mathcal{N}, \succeq \rangle$, where $\Pi(\mathcal{P})$ is a partition of $\mathcal{P}$, $\Pi(\mathcal{P}) = \{C_1, \ldots, C_M\}$ and $\succeq \triangleq \succeq_e, e \in \Pi(\mathcal{P}) \cup \mathcal{N}$ is the preference profile. Our coalitional matching game consists of: i) grouping patients into coalitions based on their location in real-time; coalitional game, ii) and then attributing one nurse to each coalition of patients based on their preferences; one-to-many matching game.

Definition 3.1: A coalitional matching in Γ is a mapping function $\mu : \Pi(\mathcal{P}) \cup \mathcal{N} \rightarrow 2^{\Pi(\mathcal{P}) \cup \mathcal{N}}$ satisfying for each coalition C in $\Pi(\mathcal{P})$ and n in $\mathcal{N}$

(a) $\mu(n)$ is in $\Pi(\mathcal{P})$ and $\mu(C)$ is in $\mathcal{N}$;
(b) $\mu(C, n) \succeq \mu'(C, n)$;
(c) n is in $\mu(C)$ if and only if C is in $\mu(n)$.

For each nurse $n \in \mathcal{N}$, $\mu(n)$ is a coalition of patients $C \in \Pi(\mathcal{P})$ along with him in the sense that this matching allows them to maximize their payoff. Similarly, for each patient p decides to belong to a coalition $C \in \Pi(\mathcal{P})$ and prefers $\mu(p)$ to maximize the profit. In each data collect period, based on their geographic location in the hospital, players define their preferences.

A. Minimum Course

The purpose behind this game is to reach fair and optimal deployment of nurses and to cover all patients in the hospital. Hence, we are interested just on the distance between different players. Neither the euclidean distance (the square root of the sum of the squares of the differences between two points x and y in each dimension) or the Manhattan distance (sum of the differences in each dimension) are appropriate to our 3D-system architecture since we deal with human movement and time and effort spent in different dimension. Indeed, we consider that the effort and time to move on the same floor (on X-axis and Y-axis) is different from that to climb or go down the stairs (Z-axis). To calculate the distance between two points, we consider the weighted euclidean distance and we introduce so-called references points r_z for each floor. The distance between two elements of our system $e_1(x_1, y_1, z_1)$ and $e_2(x_2, y_2, z_2)$ is expressed as:

$$D(e_1, e_2) = \begin{cases} d(e_1, e_2), & \text{if } z_1 = z_2 \\ d(e_1, r_{z_1}) + w.d(r_{z_1}, r_{z_1+1}) + \cdots + \\ w.d(r_{z_2} - 1, r_{z_2}) + w.d(r_{z_2}, e_2), & \text{otherwise } (z_1 < z_2), \end{cases} \quad (1)$$

where $d(A, B) = \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2}$, and w the weight attributed to the dimension-z. w can take different values depending on the scenario (the time and effort deployed to climb or go down the stairs is different form that when using the elevator).

For coalition formation, we consider split and merge rules [26] to lead rational players to form coalition structures so that the route to visit all coalition member once is minimal. The utility function/coalition value is then the sum of distances between players belonging the coalition, and the coalition formation game can be reduced to a linear programming problem:

$$\text{minimize:} \quad \sum_{e_i \neq e_j \in C} D(e_i, e_j) \quad (2)$$
$$\text{s.t.} \quad \sum_{i=1}^{|C|} U_i \leq |C|$$

U_i is a boolean variable to indicate the passage or not by the element e_i, and $|C|$ denotes the cardinal of the coalition C.

Similarly, for matching the set of patient coalitions and the set of nurses, each of them needs to identify its preferences over subsets of the other set based on the distance given in formula (1). Hence, a coalition of patients $C \in \Pi(\mathcal{P})$ prefers nurse n_j to n'_j, $n_j \succeq_C n'_j$, if the minimum calculated course to visit the coalition members by n_j, $S(C, n_j)$, is less than the minimum calculated course if the coalition is served by n'_j, $S(C, n'_j)$.

B. Fairness

Matching the set of nurse to the set of patient coalitions through the defined preference allows firmly a minimal total course and ensures a minimum time of data collect process. But, this solution may be not fair for all nurses, in the sens that in the optimum total course some nurse have more workload than others. To get fairness, we introduce Jain's fairness index which is a bounded continuous function that allows a comparison in compliance with the standard fairness benchmarks [27]. For our game we calculate this index considering all pairs matching courses:

$$\mathcal{J}(S_1, S_2, \ldots, S_M) = \frac{(\sum_{i=1}^{M} S_i)^2}{n \cdot \sum_{i=1}^{M} {S_i}^2} \quad (3)$$

The index ranges from $\frac{1}{M}$(worst case) to 1 (best case), and it is maximum when all pairwise have the same course. We incorporate the Jain's index in the coalitional matching game utility function to join efficiency and fairness.

C. Game stability

Theorem 3.1: The proposed coalitional matching game between the set of patients and the set of nurses is guaranteed to converge to a pairwise stable matching.

Proof 3.2: Let us reason by contradiction by assuming that there exists a nurse n_j and a coalition of patients C that are not in the coalition matching μ and let W the pairwise matching; $n \notin \mu(C, A)$ and $C \notin \mu(n, A)$ and there exist subsets such as $L \in W(\mu(C, A) \cup n)$ and verifying $K \in W(\mu(n, A) \cup C)$ and $L \succeq_C \mu(C, A)$ and $K \succeq_n \mu(n, A)$. Then, the nurse n was proposed to match with the coalition C but not was not chosen. So $n \notin W(\mu(C, A) \cup n)$ and thus μ cannot be stable.

D. Distributed deployment algorithm

The proposed coalitional matching game approach for dynamic and distributed data-gathering in the considered WSNB system is summarized in the algorithm 1. We consider distributed imitative Boltzmann-Gibbs learning algorithm to lead players to tend to the system stability.

Algorithm 1 Distributed deployment algorithm

Phase 1- System initialization
- Each player (nurse and patient) gets its location and discovers the system.

Phase 2- Coalition formation and preferences identification
- Split and merge rules to form coalition structure
- Patient coalition set and nurse set identify the list of preferences

Phase 3- Patients-nurse matching
- For each pairwise calculate the course
- Calculate the sum of all pairwise course and the Jain's fairness index
- Observe and evaluate the realized vector of utility

Phase 4- Learning update equation
- Update coalition matching strategy according to equation 5.

Until
- The convergence of the learning algorithm to the stable colaitional matching.

The equation for the update can be expressed like below [25],

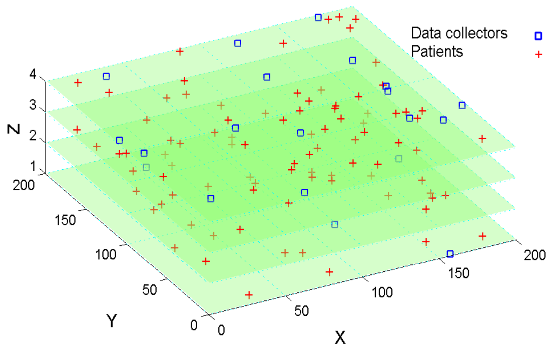

Fig. 3: A scenario of 10 nurses/data-collectors and 50 patients at the beginning of a data collect period

$$\begin{aligned} A_i(W_i) &\quad : \\ x_{i,t}(s_i, W) &= \frac{x_{i,t-1}(s_i, W)(1 + v_{i,t}(s_i))^{-y_{i,t-1}(s_i,W)}}{\Sigma_{r'} x_{i,t-1}(s_i, r')(1 + v_{i,t}(s_i))^{-y_{i,t-1}(s_i,W')}}, \end{aligned} \tag{4}$$

with $y_{i,t-1}(s_i, W)$ is the invert of the utility received.

$$y_{i,t-1}(s_i, W) = \frac{1}{U_{i,t-1}(s_i, c)}, \tag{5}$$

where $x_{i,t}(s_i, W)$ is the probability of choosing the pairwise matching W by the player i being in state s_i Also, $v_{i,t}(s_i) 0$ is the learning rate takes into account how many times the same action has been chosen, is defined by:

$$v_{i,t}(s_i) = \frac{1}{1 + \Sigma_{t'=1}^{t} \mathbb{1}_{\{a_{i,t'} = s_i\}}}. \tag{6}$$

IV. Numerical Results

We consider a hospital with an area of 200m*200m and 4 floors. "Fig. 3" shows a scenario dense of 10 nurses and 50 patients random distribution in the hospital. To evaluate the coalitional matching game approach and in order to reduce the simulation time and to obtain clear and simple plots, we consider a scenario of two nurses and three patients (167940 possible strategies for 3 nurses and 10 patients). We note that it is proofed that our proposed game converges to stable pairwise coalitional matching for all players number, and by using the distributed imitative Boltzmann-Gibbs learning algorithm that enables players to learn the stable strategy. For the considered scenario, the players coordinates are: $n_1(23, 21, 4)$, $n_2(139, 52, 2)$, $p_1(71, 13, 1)$, $p_2(84, 32, 3)$, $p_3(102, 121, 40)$. Sine we consider that a nurse should have at least one patient for fairness reasons, we obtain 6 possible pair of strategies:

$$\begin{array}{ll} W_1 = \{\{n_1, p_1, p_2\}, \{n_2, p_3\}\} & W_2 = \{\{n_1, p_3\}, \{n_2, p_1, p_2\}\} \\ W_3 = \{\{n_1, p_1, p_3\}, \{n_2, p_2\}\} & W_4 = \{\{n_1, p_2\}, \{n_2, p_1, p_3\}\} \\ W_5 = \{\{n_1, p_1\}, \{n_2, p_2, p_3\}\} & W_6 = \{\{n_1, p_2, p_3\}, \{n_2, p_1\}\} \end{array}$$

Firstly, we are interested to the probability to converge to the stable matching. "Fig. 4" shows the probability to choose W_1 by n_1 and n_2. The algorithm converges in the iterations 16, nurses choose this matching pair with probability equals $\sigma(n_j, W_1) = \{0, 0.4805\}$. In "Fig. 5" we plot the stable state learning for the second nurse. The matrix bellow corresponds to strategies distribution probability in the stable state.

$$\sigma(W_k, n_j) = \begin{bmatrix} 0 & 0.4805 \\ 0.6616 & 0 \\ 0 & 0.4382 \\ 0.3384 & 0 \\ 0 & 0.0813 \\ 0 & 0 \end{bmatrix}$$

"Fig. 6" illustrates the overall system performance with and without fairness purpose. The system performance in terms of minimum total course, coverage, and data-collect duration is better when we omit the fairness criterion and then the coalition-matching pairwise W_3 is the most effective in this case. The pairwise W_1 gives better system performance in terms of minimum total course, coverage, data-collect duration and workload fairness. The coalition-matching pairwise W_6 represents the worst case either the fairness is considered or not.

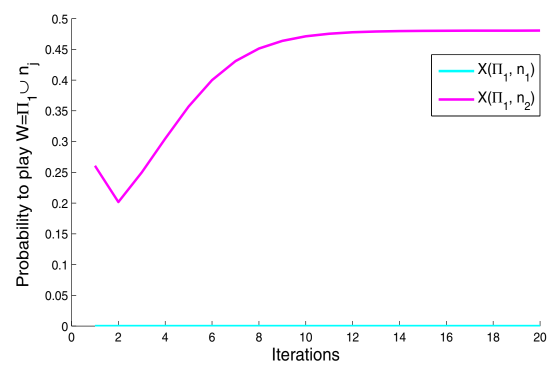

Fig. 4: The probability to play pairwise coalitional matching $\Pi_1 \cup n_j$, $j = 1, 2$

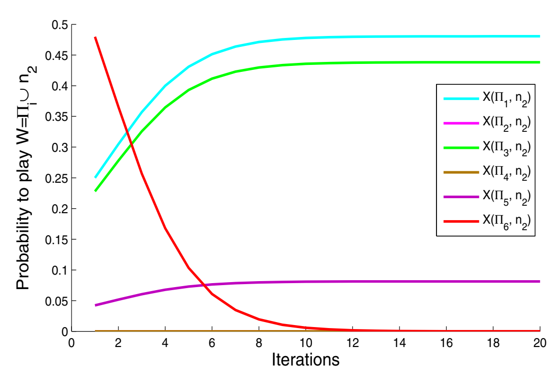

Fig. 5: The probability to play pairwise coalitional matching $\Pi_i \cup n_2$, $i = 1, \ldots, 6$

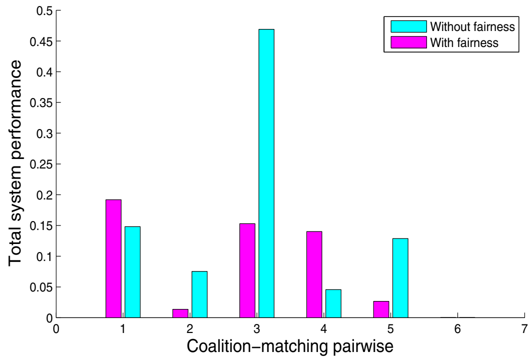

Fig. 6: The overall system performance with and without fairness purpose

V. Conclusion

This paper focuses on the design of dynamic data-gathering in WBSN system based on coalitional matching game theory. It aims to extend the Model driven derivation and verification approach that is constitute a robust and reliable approach for the construction and maintenance of WBSN systems. Our WBSN architecture consists of a set of patients randomly placed in the hospital wards, and a set of nurses equipped with data collectors to periodically gather the measured data from sensors. The purpose of this paper is how to dynamically and effectively appoint and deploy the nurses in the hospital to gather the measured data in minimal time. A formal strategy is proposed to achieve the dynamic deployment of data collectors in the WBSN system. This solution may ensure fair workload for all data collectors and aim to identify the minimal course for each data collector in the WBSN. We formulated the problem as a coalitional matching game to establish coalitions of patients and data collectors. The cooperative character of our data-gathering game allows that the overall system performance in terms of total patients coverage, nurse workload fairness and the optimal course to serve patient in each data collect period can be reached in the stable matching obtained mathematically and under distributed learning algorithm. This coalitional matching game approach is used to upgrade our architecture model and reach a total patients coverage, workload fairness and optimal total course.

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