Pilot Prototype of Autonomous Pallets and Employing Little's Law for Routing

Afshin Mehrsai, Hamid-Reza Karimi, Klaus-Dieter Thoben and Bernd Scholz-Reiter

Abstract Application of autonomous control for shop-floor scheduling by considering real-time control of material flows is advantageous to those assembly lines with dynamic and uncertain circumstances. Among several potential processors with computing and communication capabilities—for representing autonomous material carriers—wireless sensor nodes seem as promising objects to be applied in practice. For realizing autonomy in making scheduling and routing-control decisions some methodologies need to be embedded in the nodes. Among several experimented methodologies, e.g., artificial intelligence, genetic algorithm, etc., in the context of a doctoral research, in this current special case of assembly scenario, the queuing theory and its simple equations seem quite suitable. For instance, employment of Little's law for calculating and analysis of simple queuing structures is a favorable method for autonomous pallets in real shop-floors. Concerning the simplicity and inexpensive computing loads of such a rule, it suits the best to the low capacity wireless sensors in developing pilot prototypes of autonomous carriers. Little's law can be used to estimate the current waiting times of alternative stations and try to find a non-decreasing order of operations to improve the performance record (e.g., makespan) of the entire assembly system. To develop a pilot prototype, some wireless sensors—representing pallets in practice—are connected to a simulated assembly scenario via the TCP/IP protocol to evaluate the feasibility of realizing autonomous pallets in the practice of shop-floor control. Nevertheless, wireless nodes are distributed objects, so the use of data sharing for transferring low data between each other and respectively low energy consumption is necessary.

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H. Kotzab et al. (eds.), *Dynamics in Logistics*,
Lecture Notes in Logistics, DOI 10.1007/978-3-319-23512-7_10

Keywords Autonomous pallets · Shop-floor real-time scheduling and control · Prototype with simulation · Queuing theory · Wireless sensor nodes

Introduction

The exploration of those objects with autonomous control in production and logistics activities has been an interesting topic for scholars in the recent decade. It is also known that planning, scheduling, and control span have three major levels in organization and material flow planning as: strategic, tactical, and operational in logistics and production environment (Bilgen and Günther 2010). Regarding the complexity of material flow scheduling and control in the operational level, autonomous control can be potentially examined for employment in this microlevel of decision making with local perceptions and problem-solving approaches. Among several manufacturing problems, shop-floor (assembly lines) scheduling is a well known one for academics and practitioners. Indeed, the flow control of materials through stations based on a given (conventional) schedule is not always a competent solution; this is particularly true, when the operation circumstance is turbulent and dynamic and affected by uncertain factors. On this basis, the employment of autonomous carriers for moving (semi-)finished materials from a station to another one within a (close to) real-time control manner is a proficient research for practitioners. Introducing the concept of autonomous pallets in simulation experiments by Mehrsai et al. (2013) shed the light to further developments in bringing this concept closer to practice. In other words, there is not a wide range of potential objects in a production logistics environment with lasting capability for a long time in the system than can be suitable for undertaking the passion of autonomous control in practice. By looking into the details of likely candidates with this capability, products themselves and material carriers (e.g., container, pallet, jig, fixture, etc.) can undertake the merit of self-organization. While self-organized products may be more beneficial to products' users, material carriers engaged in production logistic activities are more applicable for manufacturers. Therefore, the idea of making a pilot prototype for autonomous pallets, which can run throughout a production line and autonomously control the flow of materials is desired and followed in this paper.

For this purpose, a comprehensive research was necessary to investigate alternative technologies and methodologies for supporting the occurrence of this favorite desire. In terms of technology, the state-of-the-art in ICT gradually facilitated the realization of autonomous agents in research labs with some experimental implementations. Radio frequency identification (RFID) and wireless sensor nodes (WSNs) are two exemplary technologies using mobile techniques for data storage as well as processing, respectively. These are competent candidates for pilot prototypes; however, RFID is not suitable for those missions with necessary distributed computing. Thus, WSNs are considered for representing autonomous pallets in this chapter. Accordingly, among several methodologies for inspiring the intelligence and computing capabilities to autonomous objects in shop-floors, e.g., artificial intelligence, Little's law in queuing theory seems very appropriate. Because this theorem needs low computing capacity and its algorithm is very simple, which make it suitable for WSNs. Indeed, the main contribution of this paper refers to the application of Little's law in WSNs for locally modeling and analyzing queuing systems by distributed pallets in an assembly system. The introduction to WSNs and the explanation of equations are just briefly mentioned.

The rest of the paper covers a short explanation about WSNs. Following that a description of the pilot prototype for autonomous pallets with the connection to a simulated assembly scenario is given. The queuing theory with the focus on Little's law is purposefully explained in the next section. The developed algorithms for real-time connection to the simulation scenario and the implementation of Little's law in WSNs are described later. Afterwards, the developed assembly scenario is elaborated in detail. Thereafter, the results out of the real prototype are illustrated and compared with other alternative methods, reported in previous academic papers. Finally, the summary and future of the work are described.

WSNs for Mobile Autonomous Objects

One of the most abundantly used technologies to carry the mission of data storage (for external processing) is RFID, which is currently very much applied in industrial applications, e.g., for tracking materials and identification purposes. The advantages like cheap price, relatively reasonable storage capacity, tags with flexibility forms, and adjustable applications make the RFID technology quite suitable for intelligent products toward the autonomy concept. This issue is recently addressed in autonomous product studies by CRC 637 research cluster at the University of Bremen, see www.sfb637.uni-bremen.de. However, RFID tags as pure data collection memories are clustered in the category of passive computing objects with no self-computing capability. This fact makes the variety of RFID as impractical means to be used by autonomous controlled objects for self-organization. On the contrary, WSNs are another means of ICT, investigated by CRC 637 research cluster for autonomous controlled objects, see Fig. 1. If the logistics objects can be generally classified into single items (e.g., products), packages and material carriers (e.g., pallets), and transportation means (e.g., container, forklift trucks), RFID and barcodes can be used for the single items, WSNs for packages and carriers, and GPS/cellular networks for transportation means (Son 2011).

In the recent years, employments of WSNs are increasing in many aspects of modern lifestyles. Those applications have motivated the researchers around the world to attempt to this field for investigating the quality of service (QoS) and performance of networks for more efficiency improvement. Usually, WSNs are supposed to be used in harsh environments; consequently, the performance metric evaluation of real situations is difficult. These WSNs have some capabilities, which

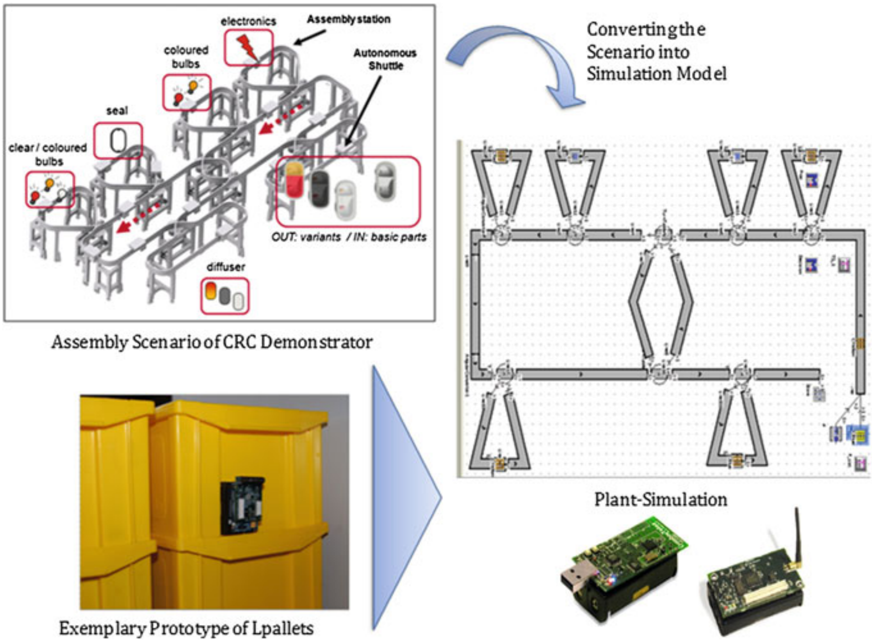

Fig. 1 Integration of WSNs representing autonomous pallets in the rare light assembly scenario of CRC 637, using simulation, WSNs, and TCP/IP protocol

made them suitable to be employed by the project of intelligent containers in the same research cluster mentioned above. Among some competencies of WSNs, their capabilities in collecting and processing data, interacting with their environments via sensors, communicating with each other, and monitoring other objects, to be directly used in logistics operations, all have underlined this state-of-the-art ICT. For more information about the WSN (Telos) see Polastre et al. (2005), Ruiz-Garcia et al. (2009).

An important issue on the application of WSNs in real-time autonomous pallets is to determine the approximate physical location of objects at any given time and local calculation. The knowledge of the location of the nodes presents the opportunity of providing location-dependent services. Also the information embedded in the packet sent from each node in WSNs contains the location of the corresponding node and the computing task. Therefore, the number of nodes and their consumption power has effects on computing power and memory size, which should be considered in real applications (Farahani 2008). Accordingly, data sharing between the nodes is another important issue in saving energy and computing expenses, since every node observes its location and may share its perception with other nodes to reduce complexity. Thus, data sharing supports the desire of computing simplicity as a decisive factor in energy saving. WSNs, representing autonomous pallets in an assembly system, must monitor local key performance indicators

(KPIs) and transmit them to the other active and (/or in sleep mode) nodes to keep continuity of data sharing, while keeping autonomy of nodes. All this needs to be more elaborated in further works.

Prototype of Autonomous Pallets with WSNs

For developing a prototype of autonomous pallets it was decided to employ wireless nodes with limited computation as well as communication capabilities (with WLAN technology). This importance took place by means of connecting real WSNs directly to an already developed simulated assembly scenario in a discrete-event manner. In doing so, the simulated model in Plant-Simulation package is integrated to some WSNs, each of which represents an autonomous pallet in the assembly scenario. This integration is done, thanks to the TCP/IP (a communication protocol) socket with the purpose of real-time synchronizing and experimenting on the performance of real WSNs in rendering control decisions in assembly line environments, see Fig. 1. In addition, Fig. 2 displays the monitoring package of the connected WSNs to each other and to the simulation for data sharing as well as connecting to the TCP/IP socket. There is one node among all which does the mission of data transfer from and to TCP/IP socket and all others share own data with that node. This monitoring package developed by Son, to centrally observe the

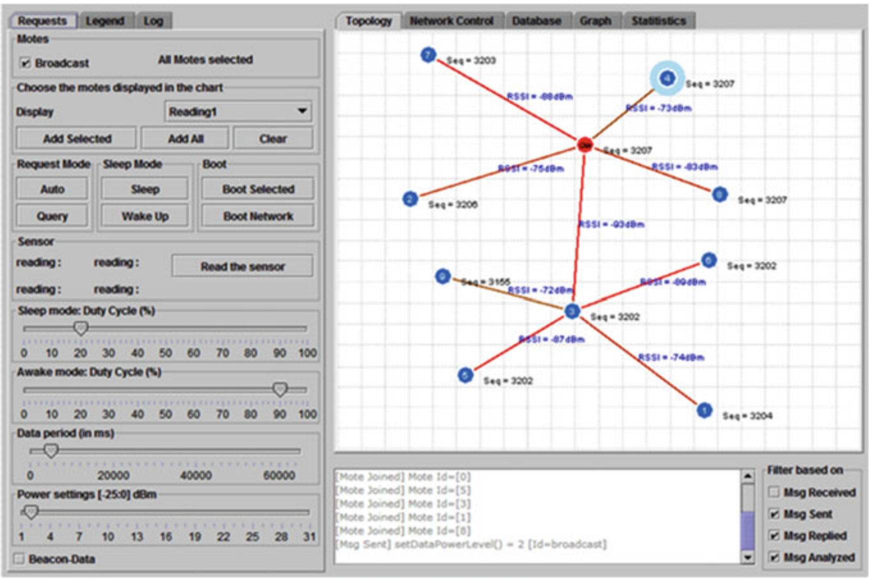

Fig. 2 A Java-based control system for monitoring the performance of connecting WSN by means of TCP/IP (Son 2011)

performance of distributed WSNs in terms of power supply, strength of data transfer, proper communication, and so forth, within an open environment, see Son et al. (2010), Son (2011). The details of the applied communication protocols between WSNs are not covered in this paper. But, the developed algorithm for connecting WSNs to the simulation-scenario and the methodology for autonomous pallets, using Little's law, should be explained in detail. Next section, concisely deals with the queuing theory pertinent to Little's law for modeling and analyzing the assembly system as a queuing system and later it defines the algorithms.

Little's Law in Queuing Theory

Queuing theory is a branch of probability theory that emerged almost one century ago, also known as traffic theory, congestion theory, theory of mass service, and theory of stochastic service systems (Cooper 1981). It is an analysis mathematical tool for studying the relationships between congestion and delay by defining derivation of characteristic quantities such as throughput time (TPT) and waiting time, in those of systems with some jobs to be processed, served, and buffered, e.g., communication systems, banking systems, and production systems. A queuing system can be recognized by three important characteristics as: the input process, the service mechanism, and the queue discipline. Basically, queuing systems are based on stochastic processes like the Markov process (Ouazene et al. 2013).

Applied notations

Notation	Description
ρ_i	Load at station i
λ_i	Total arrival rate at station i
ε_i	Service rate of a single server at station i
μ_i	Total service rate of all servers in station i
L_{qi}	Mean queue length of station i
W_i	Mean waiting time for station i
V_i	Mean system time
MPS	Master production schedule
WS	Work station
WN	Wireless node

The Markov chain is a special case of the Markov process with discrete state space and time. A well-known example for the Markov process is the special process of birth and death (BD) (Gross et al. 2008). Within BD process, transitions occur only to direct neighbors. $\{A_t\}$ counts all the arrivals and $\{D_t\}$ counts all the departures up to the time instance t. Thus, $\{N_t\} = \{A_t\} - \{D_t\}$ is a homogeneous stationary BD process with transition probabilities of $pij(h)$. For more illustration, the state transition diagram of one dimensional BD process is depicted in Fig. 3.

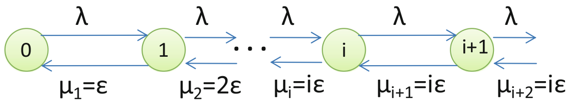

Fig. 3 Finite state process as special case of a BD process

However, the state transition diagram can be depicted when the system is in the discrete-time domain. For instance, M/M/i describes a station with i servers with Markovian arrival $\lambda = \lambda_i; \forall i \in I$ as well as service process. Then in this case from the i + 1 state, the queue is built up and then this equation holds true $\mu_i = \mu_{i+1} = \mu_{i+2} = \ldots$. Here, the notations like λ is the arrival rate that follows the Poisson distribution, $\mu = n\varepsilon$ stands for the general service rate of a station, ε is the service rate of one server in the station, and $\beta = \frac{1}{\varepsilon}$ denotes the mean service time for one server n = 1.

Generally, there are some KPIs for evaluating the performance of queuing systems, e.g., arrival rate, waiting time, and service rate (Ravindran 2008; Dombacher 2009). Among several evaluation disciplines, Little's Law (1) is a general key for modeling and analyzing queuing systems, since this is a general law and it is not specified for any particular arrival or service distributions, queuing discipline, or number of servers. With respect to the space limit just necessary equations are described. In addition, when the system is in a steady state situation the following equations can be used (i.e., in case of a single server in each station).

$$L_q = \lambda W_q \tag{1}$$

$$L_q = \frac{\rho^2}{1-\rho} = \frac{\lambda^2}{\mu(\mu-\lambda)} \tag{2}$$

$$V = \frac{1}{\mu - \lambda} \tag{3}$$

$$W_q = \frac{\lambda}{\mu(\mu-\lambda)} \tag{4}$$

$$\lambda_i = \rho_i \varepsilon_i \tag{5}$$

Methodology and Synchronization

The procedure of connecting WSNs to the simulation scenario can be shortly described by the algorithm shown in Fig. 4a. Concerning the limited memory and computing capacity, at this level of prototype-development just a simple algorithm inspired by Little's law is employed. Each node, representing an autonomous pallet, collects information about waiting time at every station and builds a list of waiting

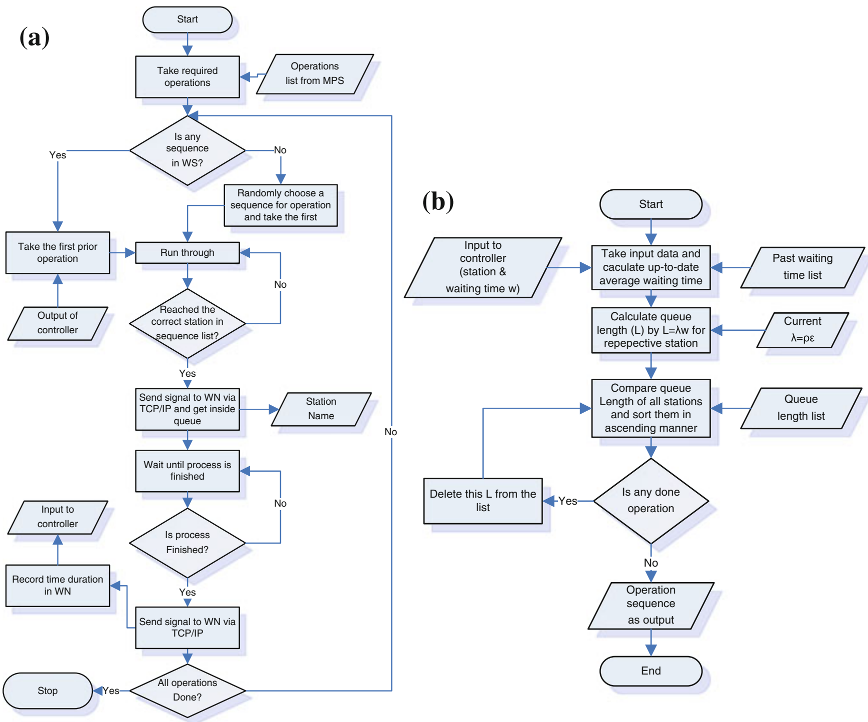

Fig. 4 **a** Processes of connecting WN as autonomous pallets to the assembly scenario. **b** Chart of Little's law controller inside WNs for choosing the next operation in real-time sequencing

times in each visiting event from every station. This leads to a matrix of waiting times collected in different events. In this regard, each autonomous pallet derives the length of queues for every station according to the moving average value of the experienced waiting times (in several round trips) for each station and the current service rate of each station by using (5) and (6).

$$L_i = \lambda_i W_i \tag{6}$$

where ρ_i is the current record of utilization for station i, and ε_i is the service rate of station i, which is considered constant over the simulation horizon. Eventually, according to the real-time values about the utilization of each station every WN approximates the queue length for the respective station. Upon that a priority list (sequencing) for operations can be configured. However, this sequence list is dynamic and after completion of each operation it is recalculated according to the current situation of the system (utilizations and waiting times). Figure 4b defines the procedure of calculating and controlling the operations' sequences inside WNs. This algorithm must be run in front of each single station to update the sequence of the remaining operations and choose the best station for that moment.

Assembly Scenario

Generally, five (5) working stations are assumed for the assembly line that build, together with one (un)load station, a closed-loop network of stations, see Fig. 5. Three (3) final product types are imagined to be assembled and delivered from this system. The number of operations O_{jm} of a job (a semi-finished product) j is equal to the machines' number m, so that each operation is assigned to a specific machine and they visit each machine only once. Thus, there are five (5) operations to be done for each job. Although, the incoming jobs have freedom in selecting the operations' number (sequence) from 1 to 4, and there is a fixed constraint in the last operation. It means the last operation must be machine number 5 or 1, because of the design-restrictions in the assembly system. Moreover, if the last operation is number 1, then the previous operation of that must be done on the machine 5. For the assembly network and the possible permutations for jobs' sequences see Fig. 5. Indeed, with regard to the probability fact of $P(A \cup B) = P(A) + P(B) - P(A \cap B)$, the mentioned constraint in the operations' sequences results in $(4! \times 1! + 3! \times 2! - 3!) = 30$ possibilities for allocating jobs' operations to the m machines. However, if this restriction did not exist the number of permutations with respect to the combination $\binom{S+K-1}{S-1}$, where S defines the number of station and K denotes product types, would result in $7!/(4! \times (7-4)!) = 35$ permutations. Furthermore, the distributed structure of this problem in terms of machines and pallets, besides the stochastic nature of all processes make this allocation problem a case of a complex real-time scheduling over the simulation time horizon.

Each single supply of semi-finished products arrives spontaneously with a stochastic manner to the un-/load station. In practice, the semi-finished products (replenished externally) are moved through the stations by means of pallets and they have to be promptly released to the system with real-time dispatching decisions. Generally, this assembly scenario follows the Conwip material flow control

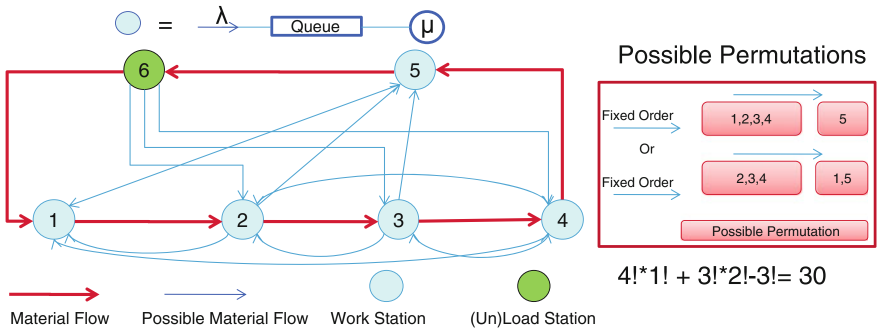

Fig. 5 Simulated assembly scenario on the *left* and the permutations for each job's order (sequence) on the *right*

by means of pallets, i.e., a pallet carries one job (semi-finished product) throughout the network and unloads at the unload station and takes another available job from that station in the next round, see Mehrsai and Scholz-Reiter (2011). Here, different alternative scenarios based on material replenishment and processing times are examined. Variable (stochastic) and constant intervals in the replenishments—between supplies of semi-finished products to the entrance (un/load station)—as well as the unbalanced processing times are the considered alternatives (scenarios). The scenarios are defined with the intention of evaluating the performances of autonomous pallets under different circumstances. Furthermore, the working time, the waiting time, and the blocked time of each station as well as the average flow time (AFT) of finished products and the makespan (completion time of last product) of all orders (150 each type) are the criteria to be compared. Here, the blocked time is the time that a product is asking for operation on a machine, while the machine is busy. In contrary, the waiting time is the time that a machine is waiting for a product to be processed. Table 1 shows the conditions of the three alternative scenarios.

Results of Synchronizing the Prototype and Simulation

Table 2 depicts some numerical data derived from Little's law for the aforementioned hybrid flow-open shop scheduling problem. Besides, these are compared against similar performances out of a conventional dispatching rule: first-in-first-out (FIFO) as well as an intelligent control system—for each autonomous pallet—out of radial basis function neural network (RBFN), see Mehrsai et al. (2013). The superiority of Little's law in simply estimating the direct waiting times, and correspondingly the order of operations can be recognized. The performance records for each station encompass the utilization percentage (working, waiting, and blocking), AFT of every pallet in one round of the assembly network, and the makespan of all jobs.

The results out of Little's law are quite comparable with RBFN and even show a slightly better performance. This can be explained by the simple procedure of this strategy and the direct calculation of waiting times instead of learning and inferring them in case of RBFN. It can be judged that, because of the simplicity of the scenario in this specific case, the straightforward strategy requires no complex and long-term learning procedure; it presents in turn better outputs. Note that application of Little's law with its simple structure is applicable to particular problems with exclusive simple structures, whereas learning pallets with RBFN can be universally used in complex systems with intelligence for rendering decisions.

Table 1 Examined scenarios with the three alternatives

Scenario	Process time of each station					Supply inter-arrival time for a type					Setup time				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1	Neg. Exp with ß = 10 min, for all					Neg. Exp with ß = 50 min, for all					5 min, for all				
2	Neg. Exp with ß=10 min, for all					Constant 50 min					5 min, for all				
3	ß1 = 8	ß1 = 8	ß1 = 8	ß1 = 10	ß1 = 8	Constant 45 min					5 min, for all				

Table 2 Examined scenarios with the three alternatives, using Little's law, compared against using FIFO and RBFN, see Mehrsai et al. (2013)

Station	1	2	3	4	5
Scenario 1 with Little's law					
Working (%)	52.36	59.23	58.08	56.15	55.33
Waiting (%)	25.17	19.48	20.10	21.25	22.46
Blocked (%)	22.47	21.30	21.82	22.60	22.21
AFT	2.91 h		Makespan		5 day + 7 h + 33 min
Scenario 1 with RBFN					
Working (%)	60.97	54.82	58.41	55.73	53.45
Waiting (%)	19.36	25.77	21.67	23.91	26.7
Blocked (%)	19.67	19.42	19.92	20.36	19.86
AFT	3.06 h		Makespan		5 day + 12 h + 37 min
Scenario 1 with FIFO					
Working (%)	53.66	52.83	54.95	54.49	59.85
Waiting (%)	24.84	25.67	23.55	24.01	18.64
Blocked (%)	21.5	21.5	21.5	21.5	21.5
AFT	3.04 h		Makespan		5 day + 15 h + 39 min
Scenario 2 with Little's law					
Working (%)	54.84	61.09	54.61	57.86	57.58
Waiting (%)	24.22	17.71	25.55	21.00	20.96
Blocked (%)	20.94	21.20	19.83	21.13	21.46
AFT	2.94 h		Makespan		5 day + 8 h + 08 min
Scenario 2 with RBFN					
Working (%)	57.28	57.66	61.7	57.5	57.72
Waiting (%)	21.13	22.63	15.61	21.17	20.24
Blocked (%)	21.59	19.71	22.69	21.33	22.04
AFT	3.18 h		Makespan		5 day + 8 h + 33 min
Scenario 2 with FIFO					
Working (%)	55.54	54.29	57.54	54.14	50.5
Waiting (%)	16.99	18.24	14.99	18.39	22.03
Blocked (%)	27.47	27.47	27.47	27.47	27.47
AFT	3.49 h		Makespan		5 day + 16 h + 31 min
Scenario 3 with Little's law					
Working (%)	50.45	49.16	53.25	64.95	49.52
Waiting (%)	25.29	28.15	23.63	11.15	26.71
Blocked (%)	24.27	22.69	23.12	23.91	23.76
AFT	2.87 h		Makespan		4 day + 20 h + 25 min

Summary and Future Work

This paper aimed at explaining the initial attempts for a pilot prototype representing the idea of autonomous pallets, utilized for real-time material flow control in shop-floors. This importance took place by employing WSNs and Little's law out of queuing theory for making sequencing decisions by every single autonomous pallet. It is demonstrated that queuing theory has the capability of modeling assembly lines even in network forms, e.g., Little's law can easily be employed by pallets for estimating queuing characteristics in assembly networks. This leads to autonomous pallets for the task of stations' monitoring as well as arranging the operations in a decentralized and real-time control manner. Therefore, to reflect the prototype feasibility of autonomous pallets, queuing theory can be competently used for approximating the general expected records of each queue. Every pallet is able to watch the service rate of each station and then based on the observed load of the station, the arrival rate for that can be estimated. Later, by having the arrival rate and the average experienced waiting time for the station—saved in the memory of WN—the estimated waiting time in that station can easily be calculated by Little's law. Furthermore, the sensitivity analysis is another capability of queuing theory in modeling complex interactive systems including servers, buffers, and customers, see Gross et al. (2008). Generally, sensitivity analysis can be explained as the study of potential changes happening to any system with uncertain variables and their effects on the conclusion and output of the system. Or, in general, it can analyze the uncertainty influences on the queuing systems' behaviors. Moreover, unlike RFID, because of the data processing capability WSNs were chosen to be employed in developing autonomous pallets.

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