INTERNATIONAL JOURNAL OF RESEARCH IN MECHANICAL, MECHATRONICS AND AUTOMOBILE ENGINEERING(IJRMMAE)
ISSN: 2454-1435 (Print) | 2454-1443 (online)
Volume 6 Issue 4, January – March 2021 - www.ijrmmae.in – Pages 77-89

DESIGN OF SINGLE STAGE ADAPTIVE KANBAN FOR HYBRID PRODUCTION SYSTEM

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Received: 12th December 2020 | Accepted: 25th March 2021

ABSTRACT

A hybrid manufacturing technology has drawn significant interests from both academia and industry due to the capability to make products in a more efficient and productive way. In this paper, we consider a hybrid production system with two distinct production lines, where one of them undertakes remanufacturing activities while the other executes traditional manufacturing tasks. The output of either production line can satisfy the demand for the same type of product without any penalties. In order to control production, we suggest a single stage pull type control mechanism with adaptive kanban and a predefined routing probability. Particle swarm optimization (PSO) simulink model and regression model are developed and used with optimization algorithms that provide minimum expected cost of adaptive kanban system. Simulink model and regression model have been observed to test the performance of the dynamic control mechanism.

Keywords: Just in Time, Hybrid production, Kanban Card, Adaptive kanban system, Markov chain, Particle swarm optimization

INTRODUCTION

The increasing technological innovation rate of products is pushing toward new profit models, based on an integrated product life cycle management. In fact, the innovative policies oriented to recover products on the one hand improve the efficiency in natural resources consumption, but on the other hand show new business opportunities to original equipment manufacturers. Among the different recovery options, remanufacturing is an important and interesting one. Remanufacturing plants show a high degree of uncertainty and complexity compared to the traditional production processes

We refer to OEMs that engage both in new product manufacturing and remanufacturing activities as hybrid production systems. The main characteristic of such production systems is that the demand is satisfied with comparable products manufactured by different facilities. Hence, both remanufactured and newly manufactured versions of a certain product coexist in the system. The demand is satisfied either with a newly manufactured product or with a remanufactured product when remanufactured products are restored to “as good as new” condition. This is usually the case for leasing systems or business-to-business suppliers of tools and machinery. In such markets, the utility and the price of the product bundled with a comprehensive warranty or maintenance contract is valued [4].

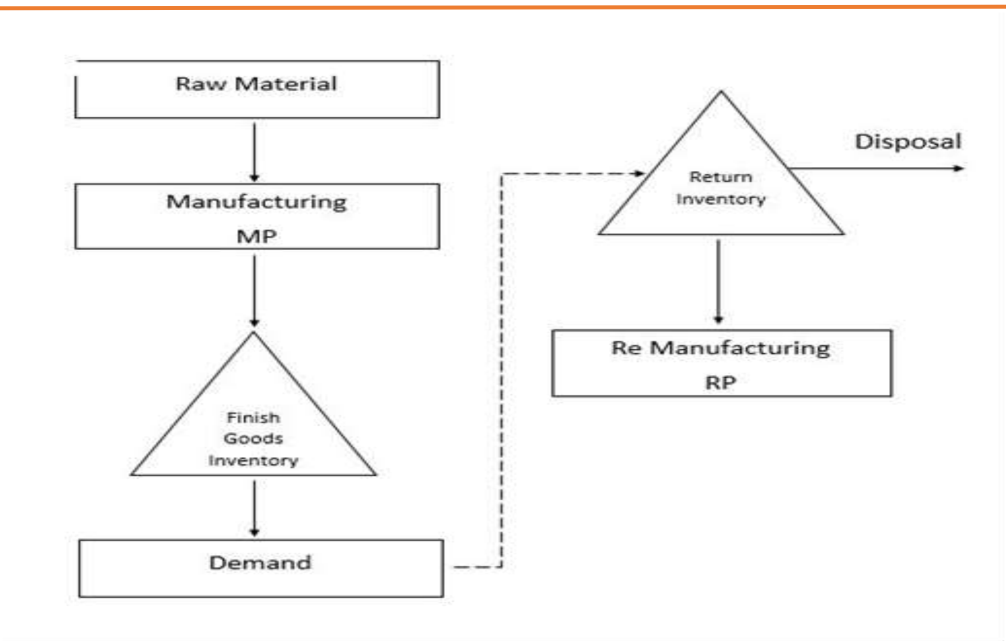

Figure 1. Hybrid manufacturing system

EXPERIMENTAL PROCEDURE

TRADITIONAL KANBAN SYSTEM (TKS)

The production control system can be generally classified into push and pull systems. The pull production system employs kanban as the controlling mechanism. In a kanban controlled production system, kanban cards are used as production orders. In the Traditional Kanban System (TKS) the number of cards used in a Manufacturing Process (MP) is kept constant. Hall (1983) proved that TKS is successful in production environment with stable demand and lead time. In order to compare the relative performance of AKS over TKS, a detailed discussion of modeling and design of TKS is presented in this chapter.

ADAPTIVE KANBAN SYSTEM

In the traditional kanban system the number of cards in use is fixed as K. Customer demand drives the manufacturing process (MP), and the demand is assumed to be stable. Each part is attached with a kanban. When a customer demand arrives, the finished part is released to the customer and the kanban attached to that part is transferred to upstream for initiating the production. The demand that cannot be met, due to non-availability of finished part, stays as back ordered demand.

PROBLEM DESCRIPTION AND MODEL

We consider a hybrid make-to-stock production system with two mutually independent processes that serve a single type of demand, where one of them manufactures new products (M) from raw materials while the other remanufactures returned items (R). All remanufactured products are assumed to be as good as new products and are stored in the finished goods inventory. Demand arrivals occur randomly and each arriving demand is satisfied with a product from the finished goods inventory. The processing times of both new and remanufactured products are also random and independent of each other.

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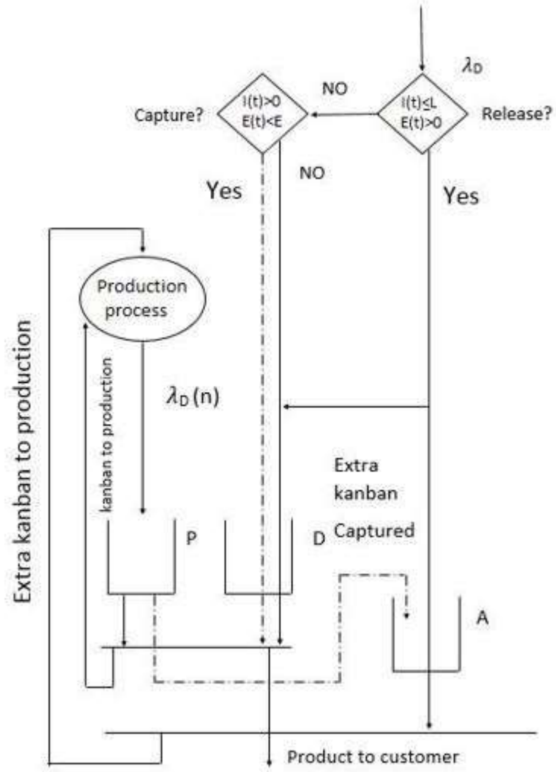

Figure 2. Adaptive control mechanism

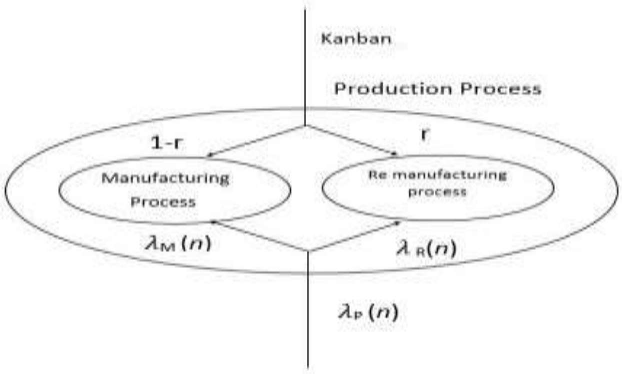

Figure 3. Production process

PARTICLE SWARM OPTIMIZATION (PSO)

Theory of particle swarm optimization (PSO) has been growing rapidly. PSO has been used by many applications of several problems. The algorithm of PSO emulates from behavior of animal's societies that don't have any leader in their group or swarm, such as bird flocking and fish schooling. Typically, a flock of animals that have no leaders will find food by random, follow one of the members of the group that has the closest position with a food source (potential solution). The flocks achieve their best condition simultaneously through communication among members who already have a better situation. Animal which has a better condition will inform it to its flocks and the others will move simultaneously to that place. This would happen repeatedly until the best conditions or a food source discovered. The process of PSO algorithm in finding optimal values follows the work of this animal society. Particle swarm optimization consists of a swarm of particles, where particle represent a potential solution

VARIANT OF PSO

Exploration is the ability of a search algorithm to explore different region of the search space in order to locate a good optimum. Exploitation, on the other hand, is the ability to concentrate the search around a promising area in order to refine a candidate solution. With their exploration and exploitation, the particle of the swarm fly through hyperspace and have two essential reasoning capabilities: their memory of their own best position - local best (lb) and knowledge of the global or their neighborhood's best - global best (gb). Position of the particle is influenced by velocity. Let x (t) denote the position of particle in the search space at time step t; unless otherwise stated, t denotes discrete time steps. The position of the particle is changed by adding a velocity, to the current position

$x(t+1) = x(t)+v(t+1)$, acceleration coefficient c1 and c2 and random vector r1 and r2.

Simple example of PSO, there is a function min f(x)

where $x(b) < x < x(a)$

x (b) lower limit and x(a) upper limit

Assume that the size of the group of particle is N. It is necessary that the size N is not too large, but also not too small, so that there are many possible positions toward the best solution or optimal Second, generate initial population x with range x (b) and x (a) by random order to get the x1, x2….xn. It is necessary if the overall value of the particle is uniformly in the search area, then it calculate the speed of all particles. All particles move towards the optimal point with a velocity. Initially all of the particle velocity is assumed to be zero. Set iteration i=1 At the iteration, find the two important parameters for each particle j that is: The best value of xj (i) (the coordinates of particle j at iteration) and declare as p best (j), with the lowest value of objective function (minimization case) f[x{j}], which found a particle at all previous iteration. The best value for all particles xj (i) which found up to the ith iteration, G best with the value function the smallest goal / minimum among all particles for all the previous iterations, Calculate the velocity of particle j at iteration i using the following formula using formula (2): Where c1 and c2 , respectively, are learning rates for individual ability (cognitive) and social influence (group), r1 and r2 and uniformly random numbers are distributed in the interval 0 and 1. So the parameters c1 and c2 represent weight of memory (position) of a particle towards memory (position) of the groups (swarm). The value of c1 and c2 is usually 2, so multiply c1r1 and c2r2 ensure that the particles will approach the target about half of the difference. Calculate the position or coordinates of particle j at the ith iteration by:

$$x_i(t+1) = x_i(t)+v_i(t+1)$$

This iteration process continues until all particles convergence the same solution. Usually it will be determined by the termination criteria (Stopping criterion), for example the amount of the excess solution with a solution now previously been very small.

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EXPERIMENTAL ANALYSIS

ANALYSIS OF THE ADAPTIVE KANBAN CONTROL POLICY ON A HYBRID SYSTEM

The above system can be modelled as a multidimensional Markov process since times between event occurrences are independent and exponentially distributed. First, consider the case where E=0. Since there are no extra kanbans, the release and capture levels of the system are no longer in effect. Therefore, the adaptive kanban control policy considered for the single-stage pull type production system in Fig. 3.1 reduces to an installation kanban control policy coordinating two independent production facilities with K kanbans in the process as discussed by Korugan and Gupta in [13]. When a demand arrives, it is satisfied by a product subject to availability. The kanban is detached and sent to RP with probability r or to MP with probability (1-r). When the arrival and service processes are as defined in the preceding section, the system follows a stochastic process, {x(t)=(xI(t), xR(t)), t>0}, where xI (t) and xR (t) denote the inventory position of the finished goods and the work-in-process inventory of RP at time t, respectively.

Let xI+(t) =max{xI(t),0}, then K−xI+(t)−xR(t) will give the work-in-process inventory of MP, as the kanban control policy limits the total number of inventory to K.

Let {P(xI,xR)} be the stationary distribution of the stochastic process

{x(t)=(xI (t),xR(t)),t>0}, where $\lim_{t\to\infty} P$ (xI (t), xR(t)) =P(xI,xR).

The conditional probability distribution for xR given xI+,xI+=max{xI,0} follows a Binomial distribution with (r,K−xI+) [11]. Thus, for E=0, the two-dimensional stochastic process reduces to a birth-death process as depicted in Fig. 4. 1.

Here, let PK(xI) denote the stationary probability distribution with K kanbans in the system. When λD/λP(K)<1, these probabilities exist and are found by solving the balance equations:

λDPK (xI)= λP (K−xI+)PK(xI−1) ,

xI∈ {−∞, ⋯0, 1, ⋯, K}, xI+ = max {xI, 0} (4.1)

$$\sum_{K}^{-\infty} P_K(x_I) = 1$$

where the total throughput of the system λP(K− x_I^+) is given as follows:

$$\lambda P(K - x_I^+) = \sum_{x_R=0}^{K-x_I} P(x_R/\,x_I^+)\left(\lambda_M(K - x_I^+ - x_R) + \lambda_R(x_R)\right), x_I = 1, \ldots\ldots, K$$

$$\lambda P(K - x_I^+) = \sum_{x_R=0}^{K} P(x_R/\,x_I^+)\left(\lambda_M(K - x_R) + \lambda_R(x_R)\right), x_I \le 0$$

$$x_I^+ = max\{x_I, 0\}, x_R \in \{0,1,\ldots K - x_I^+\}$$

$$\lambda_M(0) = 0, \lambda_R(0) = 0 \qquad (4.2)$$

The problem reduces to the calculation of the conditional probability distribution {P(xR|xI)}. As stated earlier, since each kanban detached from a finished good is routed to RP with a fixed probability r, this distribution is given as follows:

$$P(x_R|x_I) = \binom{K - x_I^+}{x_R} r^{x_R}(1-r)^{K- x_I^+ - x_R}$$

xI∈ {−∞,⋯0, 1,⋯, K }, xl+ = max{xI, 0} (4.3)

$$P(x_R|x_I) = \frac{P(x_I, x_R)}{P(x_I)} \quad (4.4)$$

The calculation of the stationary distribution {P(xR|xI)} is as follows:

$$P(x_I, x_R) = \binom{K - x_I^+}{x_R} r^{x_R}(1-r)^{K- x_I^+ - x_R}$$

xI∈ {−∞,⋯0, 1,⋯, K }, xl+ = max{xI, 0}, $x_R \in \{0,1,\dots K - x_I^+\}$ (4.5)

When E>0, it becomes necessary to add another dimension to the stochastic process to monitor the capture and release events. To this end, the number of extra kanbans xE (t) in circulation at time t is added and the stochastic process is given as {x(t) = (xI (t),xR(t), xE(t)),t>0}. The conditional probability distribution for xR given xI and xE also follows a binomial distribution and is given as

$$P(x_R|x_I, x_E) = \binom{K + x_E - x_i^+}{x_R} r^{x_R}(1-r)^{K+x_E- x_I^+ - x_R}$$

xI∈ {−∞, ⋯0, 1, ⋯, K}, xl+ = max {xI, 0},

$x_E \in \{0,1,\dots E\}$, $x_R \in \{0,1,\dots K - x_I^+\}$ (4.6)

From Eqs. (4.2) and (4.6), the state-dependent throughput of the production system is defined as follows:

$$\lambda P(K+x_E - x_i^+) = \sum_{x_R=0}^{K+x_E- x_i^+} P(x_R/ x_I^+, x_E)\left(\lambda_M(K + x_E - x_i^+ - x_R) + \lambda_R(x_R)\right),$$

xI∈ {−∞, ⋯0, 1, ⋯, K}, xl+ = max {xI, 0},

$x_E \in \{0,1,\dots E\}$, $x_R \in \{0,1,\dots K - x_I^+\}$,

$\lambda_M(0) = 0, \lambda_R(0) = 0$ (4.7)

Analogous to the E=0 case, the three-dimensional stochastic vector {x(t)=(xI(t),xR(t), xE(t)), t >0} can be reduced to the two-dimensional , {x (t) = (xI (t) , xE(t)), t > 0}, vector. When λD/λP (K + E) < 1, the limit $\lim_{t\to\infty} P$ (xI (t), xE(t)) =P(xI,xE) exists and defines the stationary distribution. The distribution is calculated by solving the following balance equations simultaneously,

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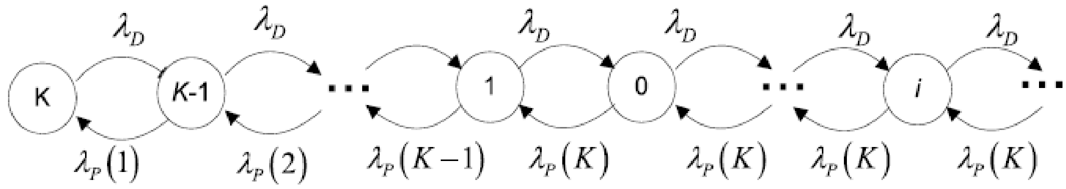

Figure. 4 The birth-death process of a general single stage Kanban control

$$\Lambda_D P(x_I,x_E) = \lambda_P\left(min\{K+x_E, K+x_E+1-x_I\}\right)P(x_I-1,x_E)$$
$$+\Lambda_D\left[\left(\sum_{i=max\{x_I,C\}+1}^{K+x_E+1} P(i,x_E+1) - \psi(x_E)\sum_{i=max\{x_I,C\}+1}^{K+x_E} P(j,x_E)\right)\right.$$
$$+\Theta(x_I)\lambda_D\left(\sum_{v=x_I}^{L-1} P(v+1,x_E-1)\right.$$
$$\left.\left. -\psi(E-x_E)\sum_{v=x_I}^{L-1} P(v+1,x_E)\right)\right]$$

$$\sum_{x_E=0}^{E-1}\sum_{x_I=L+1-x_E}^{K+x_E} P(x_I,x_E) + \sum_{x_I=-\infty}^{K+E} P(x_I,E) = 1$$

$$0 \le x_E \le E, x_I \le K + x_E,$$

$$\psi(x) = \begin{cases}0, x=0\\1, x>0,\end{cases} \quad \Theta(x) = \begin{cases}0, x \ge L\\1, x<L\end{cases} \qquad (4.8)$$

where, $P(x_I,x_E)=0$ for $\forall$ (x_I,x_E) where

xE ≠ [0, E] ∪xI ≠{[K+xE,L−xE]∪[K+E,−∞]}. Then using Eq. (3.6) and { $P(x_I,x_E)$}, the stationary distribution of the three-dimensional vector, {P(xI,xR,xE)}, is calculated.

PERFORMANCE MEASURES

In the section 4.2, we construct the expected total cost function, based on the long run behavior of the hybrid system operating under adaptive kanban control. To this end, we first calculate the stationary distribution of the system for the state vector (x) = (xI,xR,xE). Then, we construct the expected total cost function by calculating long run averages of WIP, on hand inventory and backorder levels as functions of control parameters. In this part, we analyze the properties of the cost function with respect to these control parameters to find the parameter values minimizing the expected total cost.

THE EXPECTED TOTAL COST FUNCTION, Z(x)

Let us denote the expected work-in-process in manufacturing as WIPM(x), expected work-in-process in remanufacturing WIPR(x), expected total work-in-process of the system as WIP(x)=WIPM(x)+WIPR(x), expected finished goods inventory as I(x), and expected backorders as B(x), under the stationary adaptive kanban control mechanism with predefined values of the parameters {(K,E,r,C)}. Then the expected total cost function for this system is defined as

$$\boldsymbol{Z(x) = h_R WIP^R(x) + h_M WIP^M(x) + h_I I(x) + bB(x)}$$

Using the stationary distribution obtained in Eq. (3.8), the performance measures of interest can be calculated.

Proposition 1: The stationary distribution {P(x)=P(xI,xE)} of the two-dimensional Markov process is sufficient in obtaining all average values of measures required for the calculation of the expected total cost Z(x).

Proof: Let us first look at WIP (xI,xR,xE) = WIP(xI,xE). Since,

$$\text{WIP (xI,xR,xE)} = \sum_{x_E}^{E} \sum_{x_I=L-x_E}^{K+x_E} \sum_{x_R=0}^{n_w} n_w \, P(x_I, x_R, x_E)$$

$$= \sum_{x_E}^{E} \sum_{x_I=L-x_E}^{K+x_E} n_w P(x_I, x_E) \sum_{x_R=0}^{n_w} \frac{P(x_I,x_R,x_E)}{P(x_I,x_E)}$$

In the same way, we can show that the property holds for I(xI,xE) and B(xI,xE).

Proposition 2: WIPR(xI,xR,xE)=WIP(xI,xE)r.

Proof Since,

$$WIP^R \text{(xI,xR,xE)} = \sum_{x_E}^{E} \sum_{x_I=L-x_E}^{K+x_E} x_R P(x_I, x_R, x_E)$$

$$= \sum_{x_E}^{E} \sum_{x_I=L-x_E}^{K+x_E} P(x_I, x_E) \sum_{x_R=0}^{n_w} x_R P(x_R | x_I, x_E)$$

$$= \sum_{x_E}^{E} \sum_{x_I=L-x_E}^{K+x_E} P(x_I, x_E) \sum_{x_R=0}^{n_w} x_R \binom{n_w}{x_R} r^{x_R} (1-r)^{(n_w - x_R)}$$

$$= \text{WIP(xI,xE)r}$$

After solving the balance equation set in (4.8), the steady state probabilities for the two-dimensional Markov chain are obtained by basing the calculations on the marginal probability distribution for the synchronization station defined in the same manner as in [11]. Consider an equivalent distribution where P+(xI,xE)=P(xI,xE) for L− E < xI ≤ K + E and 0 ≤ xE ≤ E, and

$$\text{P+(L−E,E)} = \sum_{n=1}^{L-E} P(n,E) + \sum_{m=max(0,E-L)}^{\infty} P(-m,E)$$

When the value of λD/λP (K+E) < 1, these probabilities exist. Then, we use a conversion formulation,

$$P(L-E,E) = P^+(L-E,E)U^{-1} \quad (4.9)$$

Where,

$$U = \sum_{n=0}^{L-E} \frac{\lambda_D(L-E-n)}{\prod_{\rho=n}^{L-E-n} \lambda_P(L+E-\rho)} + \frac{\dfrac{\lambda_D^{max(0,L-E)}}{\prod_{t=0}^{L-E-n} \lambda_P(L+E-t)}}{1 - \dfrac{\lambda_D}{\lambda_P(L+E)}}$$

Here, for B(xI,xE), WIP(xI,xE), and I(xI,xE), the cases L − E < 0 for L ≤ 0 and L − E < 0, L − E ≥ 0 for L > 0 have to be considered in the calculation. Thus,

$$B(x_I,x_E) = \sum_{s=0}^{E}\left(\sum_{n=0}^{-(L+1)} nP(-n,s) + \sum_{n=min(L-E+s,0)}^{min(L,0)} \vdots n \vdots P(n,E-s)\right) + \sum_{max(E-L,0)}^{\infty} nP(-n,E)$$

While,

$$\sum_{max(E-L,0)}^{\infty} nP(-n,E) = \frac{\left(\frac{\lambda_D^{max(0,L-E)}}{\Pi_{t=0}^{L-E-n}\lambda_p(L+E-t)}\right)\left(max(0,(E-L)) + (0,(E-L))\right)\left(\frac{\lambda_D}{\lambda_p(K+E)}\right)}{\left(1-\frac{\lambda_D}{\lambda_p(K+E)}\right)^2} P^+(L - E,E)U^{-1}$$

While,

$$I(x_I,x_E) = \sum_{s=0}^{E}\left(\sum_{n=max(0,L=1)}^{K+s} nP(n,s) + \sum_{n=L-s}^{L} max(n,0)\,P(n,s)\right) + \sum_{n=0}^{L-E-1} nP(n,E)$$

And

$$WIP(x_I,x_E) = \sum_{s=0}^{E}\sum_{n=L+1}^{K+s}\left(min(K+E,K+s-n)P(n,s) + \sum_{n=L-s}^{L} min(K+E,K+s-n)P(n,s) + \sum_{n=1}^{L-E-1}(K+E,K+s-n)P(n,s) + (K+E)\left(\frac{\lambda_D^{max(0,L-E)}}{\Pi_{t=0}^{L-E-n}\lambda_p(L+E-t)}\right)P^+(L-E,E)U^{-1}\right)$$

COST FUNCTION PROPERTIES

Let us denote the adaptive kanban control policy as π = {(K, E,r,L,C)}. Then the expected total cost is a function of this control policy, π,

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$$Z_\pi(x) = h_R WIP_\pi^R(x) + h_M WIP_\pi^M(x) + h_I I_\pi(x) + bB_\pi(x) \quad (4.10)$$

It is enough to show that, $\boldsymbol{I_\pi(x) + WIP(x) = K_{eff}}$,where $\boldsymbol{K_{eff} = K + \widehat{E}}$ with $\widehat{E}$ being the expected number of extra kanbans used in the long run .Thus by using Proposition 1 and 2,the cost function can be rearranged as

$$\boldsymbol{Z_\pi(x) = \varphi WIP_\pi(x) + h_I K_{eff} + bB_\pi(x)} \quad (4.11)$$

Where $\varphi = rh_R + (1-r)h_M - h_I$

For fixed demand rate, as K_{eff} increase either $WIP_\pi(x)$ or $I_\pi(x)$ will monotonically increase, since $WIP(x) + I_\pi(x) += K_{eff}$. The increase in Iπ(x) will increase the service level and enable more kanbans to be dispatched to the production system resulting in a higher WIPπ(x). Similarly, the increase in WIPπ(x) will result in more finished goods to be sent to the finished goods inventory as long as the system utilization is less than one. Thus, we can expect that an increase in Keff to increase both of these average values. Inversely, when eh positive on hand inventory increases a decrease in Bπ(x) is natural. Therefore, we can conjecture that for any φ>0, Zπ(x) is a convex function of K and E, when all other control variables are constant.

When other control parameters are kept constant, an increase in the capture level, C, results in an increase on the average number of extra kanbans in use, since for an extra kanban to be captured, the finished goods inventory level has to be equivalent to C. Therefore, as C increases, Keff increases and has the effect discussed above on the expected total cost function. The effect of L is just the opposite of the effect of C. Thus, through the argument given earlier, we conclude that Zπ(x) is convex in C or in L, respectively, when all other parameters are constant.

Finally, the routing probability, r, determines the average throughput of each sub-process by directing the workload. Depending on the speed of each sub-process, either the increase or the decrease of r will increase the total production rate. When the common assumption of the remanufacturing process being faster is considered, increasing r will decrease WIPπ(x) since the workload will be processed faster. The decrease in WIPπ(x) will result in an increase in Iπ(x) since their sum is constant.

Consequently, an increase in the average finished goods inventory level will result in a decrease in the average backorders, Bπ(x). Thus, we can state that Zπ(x) is convex in r also.

CONSTRAINED USING PSO ALGORITHM

The following steps are used by the PSO technique to solve the unit commitment problem

Step 1: Initialize a population of particles pi and other variables. Each particle is usually generated randomly with in allowable range.

Step 2: Initialize the parameters such as the size of population, initial and final inertia weight, random velocity of particle, acceleration constant, the max generation, Lagrange’s multiplier (λi), etc.

Step 3: Calculate the fitness of each individual in the population using the fitness function or cost function.

Step 4: Compare each individual’s fitness value with its pbest. The best fitness value among pbest is denoted as gbest.

Step 5: If the evaluation value of each individual is better than the previous ppbest, the current value is set to be ppbest. If the best ppbest is better than pgbest the value is set to be pgbest.

Step 6: Modify the λ and α for each equality and Inequality constraint.

Step 7: Minimize the fitness function using PSO method for the number of units running at that time.

Step 8: If the number of iteration reaches the maximum then go to step 9. Otherwise go to step 3.

Step 9: The individual that generates the latest is the optimal production of each with the minimum total cost.

RESULTS AND ANALYSIS

PSO based search models developed to estimate the near optimal parameters of AKS are given in the previous chapters. A similar model is developed for TKS also and used as the base for comparison. The models are implemented using MATLAB and tested with several examples. The details of the cases used for the numerical experiment.

NUMERICAL ANALYSIS

We compare the effectiveness of the adaptive kanban policy against two other pull type policies suggested for hybrid production systems in [13] and [14]. To this end, we design a set of experiments where we fix the demand rate as λD=1 and vary the service rates of individual machines to generate system utilization rate between 0.33 and 0.83 for hybrid production system, we select the holding cost parameters such that $0 \leq -\frac{\varphi}{h_I} < 0.8,$ since φ determines the final products.

Table 1. Expected total cost for parameter values for experiments

Ex.	B	h_R	h_M	h_I	μ_R	μ_M	Z(x)
1	4	1	2	3	0.6	0.6	9.702
2	4	1	3	4	1	1	2.999
3	4	1	4	5	1.5	1.5	1.809
4	4	2	2	3	1	1	3.815
5	4	2	3	4	1.5	1.5	2.765
6	4	2	4	5	0.6	0.6	10.44
7	4	3	2	4	1.5	0.6	3.851
8	4	3	3	5	0.6	1	4.656
9	4	3	4	3	1	1.5	3.771
10	8	1	2	5	1	1.5	2.424
11	8	1	3	3	1.5	0.6	3.695
12	8	1	4	4	0.6	1	5.612
13	8	2	2	4	0.6	1.5	3.429
14	8	2	3	5	1	0.6	4.729
15	8	2	4	3	1.5	1	3.979
16	8	3	2	5	1.5	1	2.817
17	8	3	3	3	0.6	1.5	4.886
18	8	3	4	4	1	0.6	6.391

Considering both supplier- driven and customer-driven cases the values of b proportional to h_I as $0.375 \leq h_I/b \leq 1.2$.The five of the six parameters listed in the Table 5.1, we consider three levels, for the backorder cost, we consider two levels using L(2137) orthogonal array as in the Table 5.1. We also set the number of machines in remanufacturing and manufacturing processes to two per process and change machine speeds in order to observe the impact of processing rate differences between them. In order to draw a fair comparison, for each experiment, control parameter values generating lowest possible costs are calculated for each control policy.

This indicates that in both supply- and demand-driven markets, the adaptive kanban control provides significant savings. The advantage diminishes as the system utilization declines. The lowest cost decreases are observed in experiments 5, 10, and 16 where the utilization rates are 1/6 and 2/5, respectively. Even though these values are feasible, they are not adequate for a production system to sustain its operation.

CONCLUSION

In this project, we introduced an adaptive kanban control policy. In the analysis, we reduced the dimension of the state space by using probabilistic routing for demand information. Then, we showed that the reduced state space is adequate to calculate all average performance measures necessary to determine the expected total cost of the hybrid production system exactly. In the second part of the paper, we redefined the expected total cost of the system as a function of the control variables. We have developed an algorithm using PSO, to find the minimized the expected total cost of the system. To this end, a set of experiments were designed that take system utilization, imbalance between remanufacturing and manufacturing process speeds, backorder to on hand inventory cost, and WIP to finished goods inventory cost ratios into account. Simulink and mathematical model with regression modelling technique for evaluation of the performance of the adaptive kanban control policy, in hybrid manufacturing system with PSO algorithm.

We conclusion that the proposed Simulink model and regression model have been observed to be performing better to other control system by predicting lowest cost. Finally, it was noticed that there is no significance and effect of degree of imbalance in the system.

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INTERNATIONAL JOURNAL OF RESEARCH IN MECHANICAL, MECHATRONICS AND AUTOMOBILE ENGINEERING(IJRMMAE)
ISSN: 2454-1435 (Print) | 2454-1443 (online)
Volume 6 Issue 4, January – March 2021 - www.ijrmmae.in – Pages 77-89

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