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CONTROLLING SCHEDULE INSTABILITY IN HOSPITAL FOOD PRODUCTION: A CASE OF THAI PUBLIC HOSPITAL IN REMOTE AREA

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Abstract. *The demand for Thai public hospital meals did not come from a patient's choice but was medically designed by a doctor, varying on a daily individual health condition. Other than that, it also varies on individual specific health conditions, e.g., kidney disease or gout, which will create a demand for a special diet called a therapeutic diet. This type of complicated demand is known as non-stationary stochastic demand. A delay in food delivery will impact patient health. At the same time, overproduction will lead to food waste. The difference between planned and actual schedules is called schedule instability and should be minimized. Therefore, this paper proposes a lot-sizing policy for Thai public hospitals to reduce schedule instability that works well in remote areas. This remote area context received less attention from researchers compared to hospitals in urban areas. The finding shows unique production planning challenges in four public hospital case studies. A stochastic lot-sizing problem was tested under a user-friendly approach, a mixed integer linear programming, to find an optimal replenishment period and quantity that can minimize the expected total cost of a case study hospital located in a remote area. The solution was satisfactory when tested for its probability of negative closing inventory in each period. The result will benefit hospital practitioners in remote areas by improving their food production planning.*
Keywords: Schedule instability, Lot-sizing problem, Hospital food

1. **Introduction.** Hospital operations management received a lot of interest from operations researchers in many areas, including controlling and managing pharmacy-related inventory [1,2]; purchasing [3,4]; managing patient flow [5,6]; doctor-patient appointment scheduling [7,8], service quality perspectives/issues [9,10], hospital management [11]. We found only a limited number of papers on controlling hospital food production systems.

There are two primary services in the hospital where patients seek diagnosis and treatment: clinical care services can be considered a core treatment process by medical professionals, including doctors, nurses, lab, etc., while support services are derived from clinical care services such as medical supplies, medicines, and food [12].

Managing a hospital's food production is more complex and challenging, and then it might seem to provide food that meets the nutritional and medical requirements, satisfies the patients, improves morale, and is microbiologically safe [13]. A well-managed operations system and other logistics activities of meal services to hospital wards will help the

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hospital achieve both its food safety and financial goals [14]. The hospital food for inward patients can be categorized into two major groups: regular diet and therapeutic diet [15]. A regular diet accounts for most inpatient meals served with largely unrestricted nutrition required. It is a diet for all patients with no specific health condition that requires using or avoiding a particular food. Whereas patients on therapeutic diets are limited to dietary selection, increased or decreased nutrition needs, and considering some diets are restrictive by nature, e.g., gluten-free diets for those with gluten allergies or gout diets for purine restriction [16].

The Universal Cover Scheme (UCS) was introduced to Thailand in 2002 as a main social health insurance program, making most services at public hospitals free of charge, including food for all admitted inpatients [21]. In Thai public hospitals, admitted patients cannot select their meals but are medically indicated by a medical professional, which varies on a daily individual health diagnosis. This is different from the system in Western countries, e.g., in Danish public hospitals [37], where patients are allowed to select their desired meal. This nature becomes a challenge for food production since the demand for food is up to individual conditions and their arrival rate. It is even more challenging for a hospital in a remote area where kitchen staff needs to plan its Master Production Scheduling (MPS) before patients are admitted because of its location constraint. The problem is how a hospital's food production planner handles this unique demand uncertainty when planning its MPS.

Most practitioners assumed demand to be stationary when solving inventory lot-sizing problems and production control because of less complexity and less computational time [17]. Demand is stationary when probability distribution does not change over time, with an assumption that no growth or seasonality exists [18]. While non-stationary demand has no natural mean and infinite variance, also a fixed probability function cannot describe its probability of occurrence [19]. Hence, the expected demand for a therapeutic diet, especially for a hospital located in a remote area, should not be assumed as stationary since its future demand can vary from as low as zero meals if no patient is admitted on that day. Or even if patients are admitted at full bed capacity, but no admitted patients need to be restricted in nutrition, then demand will also be zero. Or it could be as high as full bed capacity if all newly admitted patients are medically diagnosed as nutrition-restricted. The conventional approach that ignores non-stationary demand patterns and the constraint from remote area contexts will expose its MPS to schedule instability.

Schedule instability is defined as a revision in the original plan, which in turn, results in different replenishment decisions in successive planning cycles caused by uncertainty in demand and supply. The impact of schedule instability will lead to a change and disruption in production operations and result in a backlogged order [20]. For the hospital food system, backlogged orders of inward-admitted patients are unacceptable since they directly impact the patient's health, especially those on a therapeutic diet. However, a decision to hold more inventory to avoid instability will have a tradeoff with a probability of expiration because of a difference in demand probability function.

To the best of our knowledge, only a limited number of papers explore the challenges and constraints faced by public hospitals in remote areas when planning food production schedules. Also, only a few papers attempted to solve the lot-sizing policy for planning hospital food in remote areas. Therefore, this paper aims to fill the gap by exploring four public hospitals in Thailand, also, to help hospital nutritionists reduce schedule instability when producing a therapeutic diet by finding a lot-sizing policy that best matches its constraints from the remote area context.

The major contribution of this paper is not only about developing a model but exploring and collecting constraints faced by hospitals in remote areas, then proposing a modification to the existing model in the literature to meet all constraints faced by Thai public hospitals in remote areas. The modified approach will test with actual data from one case study hospital to ensure all constraints and requirements are met before making this approach a policy for other hospitals under the same context.

2. **Literature Review.** As mentioned in the previous part, the demand for a therapeutic diet in Thai public hospitals should be considered a non-stationary stochastic demand when planning its production. Bookbinder and Tan [22] proposed three different strategies to deal with demand uncertainty under a probabilistic lot-sizing problem: dynamic uncertainty, static uncertainty, and static-dynamic uncertainty strategy. Dynamic uncertainty strategy is the strategy in which the decision on both lot size quantity and replenishment period is based on realized demand, while for static uncertainty strategy, replenishment period and lot size quantity are predetermined ahead of the entire planning horizon. Lastly, for static-dynamic uncertainty strategy, the lot size quantity varies upon realized demand, but the replenishment period is determined in advance of the entire horizon.

From a hospital management point of view, the dynamic uncertainty strategy is the most cost-effective strategy because of varying both replenishment period and lot size quantity upon actual demand. Still, it is a tradeoff with ignorance of hospital production constraints, e.g., the hospital's main kitchen production capacity, supplier delivery schedule, and patient serving time are fixed. For example, waiting for a medical professional's daily bedside diagnosis before determining lot size quantity in each meal may not always be practical, e.g., it might exceed production capacity or inventory for a gout diet on that day. The static uncertainty strategy will create no schedule instability but will be very costly for the hospital since it is already absorbed through a predetermined lot size quantity. Thus, this paper will use the static-dynamic uncertainty strategy even though it is not the most cost-effective strategy, but predetermining the replenishment period in advance of the planning horizon is the best fit for hospital business where patient's health is the greatest concern.

This paper aims to help hospitals reduce schedule instability in their therapeutic diet production schedule. We will need a practitioner-friendly model for solving a non-stationary stochastic lot-sizing problem. It should be in a simple linear programming form so that hospital nutritionists can use general solver software to solve in their future use.

[23] was among the most cited paper. Tarim and Kingsman proposed a model for solving a multi-period single-item stochastic dynamic lot-sizing problem with non-stationary stochastic demand shown in Equations (1)-(8). The model provided an optimal replenishment period and quantity solution under the constraint of non-negative ending inventory in each service level. Later, the model was extended into the form of a piecewise linear approximation by using Mixed-Integer Linear Programming (MILP) equivalent model [24]. It is followed by a new form of constraint programming [25]. Later, an alternative computational approach was developed using the relaxation of MILP that can be solved without the need to use any solver program [26]. Later, another form of linear relaxation of the original model was proposed to achieve better computational performance [27]. The original model was also extended with piecewise linear concave ordering cost [28]. Later was implemented in airline catering operations [29].

$$\min E[TC] = \sum_{t=1}^{n}(a\delta_t + hE[I_t] + vE[R_t] - vE[I_{t-1}]) \tag{1}$$

subject to

$$E[I_t] = E[R_t] - E[d_t], \qquad t = 1, \ldots, N \tag{2}$$

$$E[R_t] \geq E[I_{t-1}], \qquad t = 1, \ldots, N \tag{3}$$

$$E[R_t] - E[I_{t-1}] \leq M\delta_t, \qquad t = 1, \ldots, N \tag{4}$$

$$E[I_t] \geq \sum_{j=1}^{t} \left(G^{-1}_{d_{t-j+1}+d_{t-j+2}+\cdots+d_t}(\alpha) - \sum_{k=t-j+1}^{t} E[d_k] \right) P_{tj}, \quad t = 1, \ldots, N \tag{5}$$

$$\sum_{j=1}^{t} P_{tj} = 1, \qquad t = 1, \ldots, N \tag{6}$$

$$P_{tj} \geq \delta_{t-j+1} - \sum_{k=t-j+2}^{t} \delta_k, \qquad t = 1, \ldots, N, \; j = 1, \ldots, t \tag{7}$$

$$E[I_t], E[R_t] \geq 0, \; \delta_t, P_{tj} \in \{0, 1\}, \qquad t = 1, \ldots, N, \; j = 1, \ldots, t \tag{8}$$

where

$E[d_t]$ Expected demand in period t, a random variable with known probability density function.
a The fixed ordering cost.
v The fixed unit variable cost.
h The fixed holding cost.
$E[I_t]$ Expected closing inventory at the end of period t.
$E[R_t]$ Expected replenishment inventory level (order-up-to level).
δ_t Binary variable, 1 if an order is scheduled in period t, 0 otherwise.
P_{tj} Binary variable, 1 if most recent order prior to period t took place in period $t - p + 1$, 0 otherwise.
M Some large positive number.

Equation (5) is the service level constraint, the term $G^{-1}_{d_{t-j+1}+d_{t-j+2}+\cdots+d_t}(\alpha)$ represents the minimum post-replenishment inventory level in period $t - j + 1$ that is adequate to respond to the desired service level in period t. It can be calculated offline using any spreadsheet program by Equation (9). Later, this constraint was developed by adding a backlog penalty cost using piecewise linear approximation [38].

$$G^{-1}_{d_{t-j+1}+d_{t-j+2}+\cdots+d_t}(\alpha) = \sum_{k=t-j+1}^{t} E[d_k] + Z_\alpha C \left(\sum_{k=t-j+1}^{t} E^2[d_k] \right)^{1/2} \tag{9}$$

Pauls-Worm et al. [30], and later Pauls-Worm et al. [31], developed stochastic programming that included a perishability constraint by introducing a new constraint on the perishability of raw materials using a fixed maximum shelf lifetime as shown in (10)-(14) where M is the fixed maximum shelf life, Y_t is a binary variable taking the value of 1 if there is a replenishment in period t. While Z_{jt} is a replenishment cycle length j in period t aimed at fulfilling the demand for j period. Also, FIFO conditions for stock use were introduced in Equations (12)-(14). This developed model enabled the use of inventory from the previous period as long as it did not exceed a maximum shelf life (more details will be discussed in the next section). Although several papers are already extended by adding constraints to a conventional model, no paper has taken remote area conditions into their approach.

$$\sum_{j=1}^{M} Y_{t+j-1} \geq 1 \qquad t = 1, \ldots, T - M \tag{10}$$

$$Q_t \geq \sum_{j=1}^{M} (Z_{jt} \cdot LevelQ_{jt}) \qquad t = 1, \ldots, T-1 \tag{11}$$

$$E\{I_{M-1,t-1}\} - Ed_t = E\{I_{Mt}\} - A_{M-1,t} \qquad t = 1, \ldots, T \tag{12}$$

$$E\{I_{b,t-1}\} - A_{b+1,t} = E\{I_{b+1,t}\} + A_{b,t} \qquad t = 1, \ldots, T;\ b = 1, \ldots, M-2 \tag{13}$$

$$E\{R_t\} - A_{1,t} = E\{I_{1,t}\} - X_t \qquad t = 1, \ldots, T \tag{14}$$

Not only in a lot-sizing research area that has received a lot of attention from operations researchers, many papers have also tried exploring the unique hospital food operations under its location context, for example, the meals on wheels system in Australia [32], the meals on wheels in Canada [33], the homebound system for elderly patients [34], managing food waste from operations in England hospitals [35], and the processes and food quality of hospitals in Wales [36]. However, exploring food production constraints that public hospitals face in remote areas does not yet exist. Therefore, this paper would like to fill the gap in the context of a public hospital in a remote area where conditions and constraints will be explored and propose a user-friendly approach for a practitioner to implement with real data.

The next section will present data, as same as constraints collected from the case study hospitals and decide which model can help a case study hospital deal with its demand uncertainty while planning its MPS.

3. **Methodology.** This paper has selected four Thai public hospitals in a remote area (more than 2 hours away from downtown and more than 600 kilometers from the capital city) as a case study. The observation and interviews were conducted from November to December 2021 and aimed at finding the challenges and constraints faced when planning its MPS.

The survey results found an explanation on why planning a production scheduling of a therapeutic diet in a public hospital in a remote area is more challenging than in a hospital in an urban area. Firstly, Thai public hospitals in remote areas work as primary care. Any cases beyond their capability will be transferred to a higher capacity hospital in downtown. Therefore, a permanent specialized clinic or doctor for specific diseases like a Chronic Kidney Disease clinic where patients will need a therapeutic diet is unavailable as in bigger hospitals in urban areas. For example, there is no regular demand for a gout diet, but sometimes, patients with gout are admitted to the hospital because of a high fever. Then gout diet will be ordered to the kitchen, making a demand for a therapeutic demand become non-stationary stochastic.

Figure 1 shows the recorded data of the gout diet that a medical doctor ordered to the kitchen of one of the case study hospitals for the past 90 days. There is no specific gout clinic in this hospital since they are a very small hospital in a remote area, but patients admitted to the hospital for another treatment, but their health condition requires a low-purine diet, making it challenging for kitchen staff to create an optimal plan for their production schedule since it might be as high as full bed capacity, or as low as zero.

Secondly, a bigger hospital in the urban area has higher bargaining power with food suppliers for "on-demand" stock fulfillment, while a smaller hospital in a remote area has to issue a predetermined quantity of raw materials, as same as a fixed delivery schedule because of lower purchasing quantity and longer range of transport, which makes it very costly for suppliers to provide "on-demand" stock fulfillment likes hospital in urban areas.

Table 1 shows how kitchen staff from one case study hospital plan their production schedule. The expected demand for the whole week is equal to the maximum demand from the past, and order-up-to-level is equal to the expected demand, meaning they

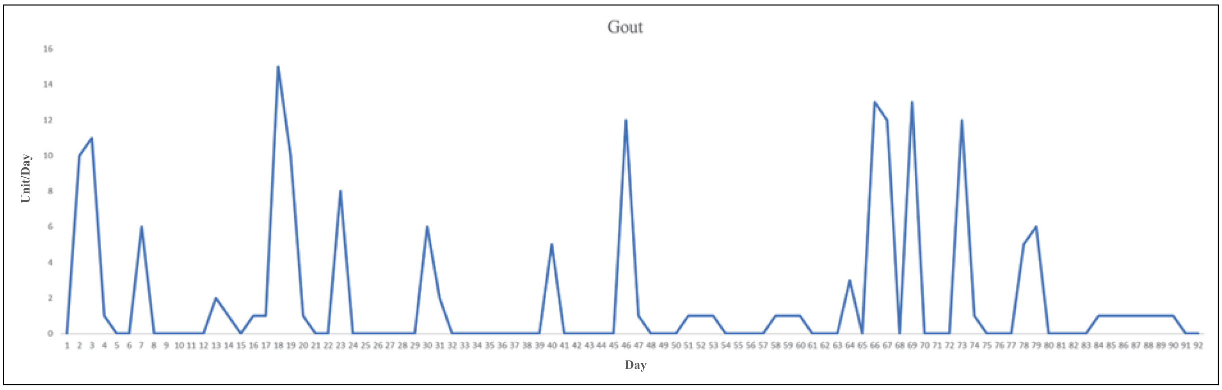

FIGURE 1. Actual demand for "Gout Diet" from one of the case study hospitals

TABLE 1. AS-IS Production plan of one case study hospital for "Gout Diet"

Menu: Gout Diet	**Day of the week**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Expected demand	**15**	**15**	**15**	**15**	**15**	**15**	**15**
Order-up-to-level	15	15	15	15	15	15	15
Planned closing inventory	0	0	0	0	0	0	0

order food suppliers to deliver daily. This is because they are a public hospital, and the government financially supports operational costs. The scheduler's pressure from the patient food shortage is higher than overstock and becomes kitchen cost. That is why they order every day; even the maximum shelf life can last two days. We found all four hospitals have the same approach when planning their therapeutic diet production schedule.

Lastly, a shortage and overstock of raw materials for a therapeutic diet in hospitals in remote areas is more costly than in urban hospitals. A shortage of raw materials for making a gout diet may cost kitchen workers 3-4 hours of driving time to buy in a city, while a hospital in urban areas only needs a few minutes. At the same time, overstock is more likely to have expired raw materials since the demand for gout diets in remote areas is less stable than in hospitals in urban areas. Therefore, perishability plays a vital role in production scheduling.

According to the mentioned constraints that made public hospitals in remote areas differ from those in urban areas, together with all existing lot-sizing policies reviewed in literature review section. This paper would like to propose modified stochastic programming under the form of MILP using the conventional model from Tarim and Kingsman [23] because of its simplicity and user-friendly enough for hospital staff. The optimal solution can be obtained using a spreadsheet program together with any commercial solver software. At the same time, the above explored remote area constraints will be added to the model by using newly developed perishability constraints from Pauls-Worm et al. [31]. A modification between both models will enable hospital staff to obtain an optimal order-up-to-level and replenishment period to minimize expected total cost under remote area conditions. The formulation and its notation are shown in Equations (15)-(36):

$$\min E\{TC\} = \sum_{t=1}^{T} \left\{ a\delta_t + vE\{R_t\} + h \sum_{b=1}^{M-1} E\{I_{bt}\} + wE\{I_{Mt}\} \right\} \tag{15}$$

subject to

$$\sum_{j=1}^{M} Z_{jt} = \delta_t \qquad t = 1, \ldots, T - M + 1 \tag{16}$$

$$\sum_{j=1}^{T-t+1} Z_{jt} = \delta_t \qquad t = T - M + 2, \ldots, T \tag{17}$$

$$Z_{1t} \le \delta_{t+1} \qquad t = 1, \ldots, T - 1 \tag{18}$$

$$j \cdot Z_{jt} \le \sum_{i=1}^{j-1} (1 - \delta_{t+i}) + \delta_{t+j} \qquad t = 1, \ldots, T - j;\ j = 2, \ldots, M \tag{19}$$

$$\delta_{T+1} = 1 \tag{20}$$

$$\delta_1 = 1 \tag{21}$$

$$\sum_{j=1}^{M} \delta_{t+j-1} \ge 1 \qquad t = 1, \ldots, T - M \tag{22}$$

$$E\{R_t\} \ge \sum_{j=1}^{M} (Z_{jt} \cdot \mathit{LevelE}\{R_{jt}\}) \qquad t = 1, \ldots, T - 1 \tag{23}$$

$$E\{I_{M-1,t-1}\} - E\{d_t\} = E\{I_{Mt}\} - A_{M-1,t} \qquad t = 1, \ldots, T \tag{24}$$

$$E\{I_{b,t-1}\} - A_{b+1,t} = E\{I_{b+1,t}\} + A_{b,t} \qquad t = 1, \ldots, T;\ b = 1, \ldots, M - 2 \tag{25}$$

$$E\{R_t\} - A_{1,t} = E\{I_{1,t}\} - X_t \qquad t = 1, \ldots, T \tag{26}$$

$$M_t \cdot BA_{bt} \ge A_{bt} \qquad t = 1, \ldots, T;\ b = 1, \ldots, M - 1 \tag{27}$$

$$M_t \cdot (1 - BA_{bt}) \ge E\{I_{b+1,t}\} \qquad t = 1, \ldots, T;\ b = 1, \ldots, M - 1 \tag{28}$$

$$M_t \cdot BX_t \ge X_t \qquad t = 1, \ldots, T \tag{29}$$

$$M_t \cdot (1 - BX_t) \ge E\{I_{1,t}\} \qquad t = 1, \ldots, T \tag{30}$$

$$E\{I_{b0}\} = 0 \qquad b = 1, \ldots, M \tag{31}$$

$$E\{I_{bt}\}, E\{R_t\} \ge 0 \qquad t = 1, \ldots, T;\ b = 1, \ldots, M \tag{32}$$

$$EA_{bt} \ge 0 \qquad t = 1, \ldots, T;\ b = 1, \ldots, M - 1 \tag{33}$$

$$X_t \ge 0 \qquad t = 1, \ldots, T \tag{34}$$

$$\delta_t, Z_{jt} \in \{0, 1\} \qquad t = 1, \ldots, T;\ j = 1, \ldots, M \tag{35}$$

$$BA_{bt}, BX_t \in \{0, 1\} \qquad t = 1, \ldots, T;\ b = 1, \ldots, M - 1 \tag{36}$$

where

$E\{TC\}$	Expected total cost in the whole planning horizon
$E\{R_t\}$	Expected replenishment quantity at the beginning of period t
$E\{I_{bt}\}$	Expected inventory level of items with age b at the end of period t
$E\{I_{Mt}\}$	Expected inventory of age M at the end of period t (Considered as waste)
T	Length of planning horizon
t	Period index, $t = 1, \ldots, T$
M	Fixed maximum shelf life time
b	Age index, $b = 1, \ldots, M$
j	Index denoting the length of the replenishment cycle
a	Fixed ordering cost for every replenishment
v	Variable unit production cost
h	Unit holding cost
w	Unit disposal cost or salvage value for item becoming waste

Z_{jt} Replenishment cycle length j in period t aimed at fulfilling demand for j period
$E\{d_t\}$ Expected demand during period t
δ_t Binary variable takes the value of 1 if there is a replenishment in period t, and 0 otherwise
A_{bt} Shortage of inventory of age b in period t
X_t Number of items short at the end of period t
β Target cycle fill rate
C Coefficient of variation

The model can be explained as follows. The objective function (15) is to minimize the total expected cost from ordering cost, unit variable cost, holding cost, and unit expiration cost over the planning horizon. Equations (16)-(21) are the order timing constraint, $\delta_t = 1$ if there is a delivery in period t, and $Z_{jt} = 1$ denotes the replenishment cycle length j in period t aimed at fulfilling demand for j periods, for period t and the next $j-1$ periods. It also requires delivery for $1, 2, \ldots, M$ period. If there is no delivery at period t, then $Z_{jt} = 0$ for all j. Equations (18)-(20) are a constraint to ensure that if a replenishment takes place in period $t+j$ ($\delta_t = 1$ and $\delta_{t+j} = 1$), and in between, there will be no order. Equations (21) and (22) are a logical constraint that, at least, an order will be delivered in the first period and every M period.

Equation (23) is a constraint to make sure that the expected replenishment quantity $E\{R_t\}$ will be greater than or equal to $LevelE\{R_{jt}\}$, a table of expected demand corresponds to the desired service level that can find from Equation (37). Equations (24)-(26) are an FIFO logical constraint for the item in stock. Equation (24) is a constraint that the oldest inventory is to be used first for demand fulfillment. Equation (25) is a fulfillment constraint that shortage will use the freshest items that have been delivered in the current period. Equations (27)-(30) are a logical constraint to make the right-hand sides of some variables in Equations (24)-(26) have a value of zero by using binary variables BA_{bt} and BX_t. And Equations (32)-(36) are definition constraints.

$$LevelE\{R_{jt}\} = \sum_{t}^{k=j-t+1} d_k + Z_\alpha C^2 \left(\sum_{t}^{k=j-t+1} d_k^2 \right)^{1/2} \quad (37)$$

This paper will integrate a more practitioner equation for finding $LevelE\{R_{jt}\}$ that provides the answer with the same constraint on fill rate but can be solved offline by any spreadsheet program. And hence $LevelQ_{jt}$ in this paper will be calculated from Equation (37) where Z_α represents the same value as desired fill rate, β, e.g., $Z_{\alpha=0.95} = 1.645$, while C is a coefficient of variation $C = \frac{\sigma}{\mu}$.

Once the constraints of four hospitals are explored, this paper collected a recorded demand for 3 therapeutic menus for 52 weeks from one case study hospital. The planning horizon's length follows its real operations, saying seven days, e.g., $t = 1$ represents Sunday. The nutritionist will plan their MPS for one week long and issue one week in advance based on their self-experience. The expected demand in this paper was found from $\mu = E(x) = \sum_{i=1}^{N} X_i P(X_i)$ where $E(x)$ is the expected value of a discrete random variable, X_i is the ith the outcome of X, and $P(X_i)$ is the probability of the ith occurrence of X. With a total of demand observed from 52 weeks and the central limit theorem, our expected value will be normally distributed. The expected demand and related parameters are shown in Table 2.

The expected demand in Table 2 represents a stochastic demand of the main ingredient (in the unit of one serving size) in each menu corresponding to its bill of material. For example, Menu 2, the Gout diet, required low-purine meat like sea brass (which is not used in other menus). Coefficient of variation, $C = \sigma_t/\mu_t = 0.2$ represents a demand

Table 2. Expected demand of the main ingredient in each menu

Menu/Period (day)	**Expected demand during period t**							**Fixed parameters**					
	1	2	3	4	5	6	7	$C = \sigma_t/\mu_t$	a	v	h	w	M
Menu 1 (Chronic Kidney Disease)	15	18	20	20	17	18	17	0.3	200	10	5	0	3
Menu 2 (Gout)	10	10	14	12	12	14	10	0.2	300	10	10	0	2
Menu 3 (Sodium Restricted Diet)	10	12	12	15	13	12	12	0.2	60	5	4	0	3

dispersion in the past 52 weeks around its mean. $M = 2$ defines the maximum storage time of 2 days for storing sea brass in the hospital kitchen. While a, v, h, and w represent ordering cost, unit cost, holding cost, and disposal costs. The problem will solve by using IBM ILOG Cplex Optimization Studio version 20.1 on a PC with 2.5GHz Intel Core i5 and 4096 MB of ram.

4. **Results.** As previously reported, three major challenges faced by hospitals in remote areas include the following. There is no regular demand for a therapeutic diet as there is no specialized clinic in a remote area hospital like a big hospital in an urban area. They all have no bargaining power for on-demand delivery fulfillment by suppliers due to small purchasing quantities relative to big hospitals. The perishability of raw materials plays a vital role due to hospital location constraints.

This paper also found that all four hospitals are very sensitive to schedule instability since they all have a very limited number of kitchen workers, as same as kitchen equipment. All four hospitals only have a maximum of two cookers, two kitchen workers (responsible for preparing raw materials and cleaning work), and two delivery staff. At the same time, the food nutritionist also needs to work as a production manager by planning and issuing MPS.

All menus are predetermined a week in advance with a policy of a single menu per each diet type. Suppose it was predetermined in MPS that a Sodium restricted diet of Monday morning would be a bowl of fish-boiled rice. In that case, any patients that medical professionals assigned have Sodium restricted diet during that time will have to take a bowl of fish-boiled rice. Because of this nature, kitchen workers have a predetermined sequence of what menu to prepare for each shift. If the expected number of fish-boiled rice is lower than the actual demand ordered by a medical doctor, a production sequence will be disrupted, including machine and worker scheduling. Unlike a big hospital with a specific kitchen for a different type of menu, with a specific kitchen worker, they will be less sensitive to schedule instability since a disruption in one menu will not interfere with the whole kitchen schedule.

All four hospitals use nutritionist self-experience to decide every value in MPS, from expected demand, quantity, and replenishment period. Not because they did not care about improvement but because their main focus was on the production of a regular diet since it covered more than 80 percent of total production with more stable demand compared to a therapeutic diet. That is why the performance of a therapeutic diet production schedule is neglected in all four hospitals.

This paper sent the expected demand of Menu 1 for the next seven days to the nutritionist of the case hospital to see how they decided the order-up-to-level (Q_t). The result is shown in Table 3 below. The explanation behind $E\{R_t\} = \{60, 0, 0, 60, 0, 0, 20\}$ is that

Table 3. AS-IS Policy of deciding order-up-to-level of case study hospital

Menu 1 (Chronic Kidney Disease)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Expected demand	**15**	**18**	**20**	**20**	**17**	**18**	**17**
Order-up-to-level ($E\{R_t\}$)	60	–	–	60	–	–	20

they consider demand in every period equal to max expected value, and the raw materials for this menu can last for 3 days ($M = 3$), that is why they will plan for 60 on period $t = 1$. Then we will see the result obtained from modified model proposed in this paper.

The first step in solving Equations (15)-(36) is to do an offline calculation for a table of desired fill rate ($LevelQ_{jt}$) by using a spreadsheet program with Equation (37). This table will be data for the solver program to deal with the demand uncertainty by listing all possibilities of demand corresponding to desired fill rate. The sample result is shown in Table 4.

Table 4. Offline solution of desired fill rate ($LevelQ_{jt}$) of Menu 1 at $\beta = 0.99$ and $\beta = 0.95$

$LevelE\{R_{jt}\}$		**Period t**													
		$\beta = 0.99$							**$\beta = 0.95$**						
		1	**2**	**3**	**4**	**5**	**6**	**7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Expected demand		**15**	**18**	**20**	**20**	**17**	**18**	**17**	**15**	**18**	**20**	**20**	**17**	**18**	**17**
j	**1**	18	22	24	24	21	22	21	17	21	23	23	20	21	20
	2	38	44	46	42	40	40	0	36	42	44	41	39	39	0
	3	59	65	64	62	58	0	0	58	63	62	60	56	0	0
	4	81	83	83	80	0	0	0	78	81	81	77	0	0	0
	5	98	102	101	0	0	0	0	96	99	98	0	0	0	0
	6	117	119	0	0	0	0	0	115	117	0	0	0	0	0
	7	135	0	0	0	0	0	0	132	0	0	0	0	0	0

Table 4 shows the offline solution solved by using any spreadsheet program for desired fill rate from $LevelE\{R_{jt}\} = \sum_t^{k=j-t+1} d_k + Z_\alpha C^2 \left(\sum_{k=t-j+1}^t d_k^2\right)^{1/2}$ of Menu 1. For example, $LevelE\{R_{21}\}$ at $\beta = 0.99$, the $\sum_t^{k=t-j+1} d_k$ will equal to the sum of expected demand from period $t = 1$ to period $k = 2 - 1 + 1 = 2$, which is equal to $33 + (2.326 \times 0.09) \times \left(15^2 + 18^2\right)^{1/2} = 38$, which means if replenishment takes place in period $t = 1$ and wants to be able to respond to the expected demand until period $t = 2$, the replenishment quantity should be 38. However, since Menu 1, the maximum shelf life period is $M = 3$, then we only need the result from the table in period $j = 1, 2, 3$.

The approach for finding results in Table 4 by using Equation (37) is user-friendly enough for hospital practitioners to use with a spreadsheet program and also enable them to adjust to any raw materials with different M value. As the same as allowing them to put desired fill rate into account when planning which was never happened before. After Table 4 is prepared for all menu items, then the optimal results solved with CPLEX are shown in Table 5.

According to the result in Table 5, if a hospital, e.g., a case study hospital, fill rate policy for Menu 1 is set to be 0.99, then the hospital nutritionist should set a replenishment period for a supplier to deliver in period $t = \{1, 4, 6\}$ with the quantity of $E\{R_t\} = \{59, 42, 40\}$. The expected inventory left at the end of period $I_{1t=1} = 44$ units will use for production

TABLE 5. Solving each service level's optimal quantity and replenishment period

Menu 1	$\beta = 0.99$							$\beta = 0.95$						
(Chronic Kidney Disease)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Expected demand	**15**	**18**	**20**	**20**	**17**	**18**	**17**	**15**	**18**	**20**	**20**	**17**	**18**	**17**
Order-up-to-level $E\{R_t\}$	59	–	–	42	–	40	–	36	–	62	–	–	39	–
Closing inventor $E\{I_{1t}\}$	44	–	–	22	–	27	–	21	–	45	–	–	21	–
Closing inventory $E\{I_{2t}\}$	–	26	–	–	5	–	10	–	3	–	25	–	–	4
Closing inventory $E\{I_{3t}\}$	–	–	6	–	–	–	–	–	–	–	–	8	–	–
Expected total cost	2,680							2,565						
Menu 2	$\beta = 0.99$							$\beta = 0.95$						
(Gout)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Expected demand	**10**	**10**	**14**	**12**	**12**	**14**	**10**	**10**	**10**	**14**	**12**	**12**	**14**	**10**
Order-up-to-level $E\{R_t\}$	21	–	15	26	–	26	–	21	–	15	25	–	25	–
Closing inventory $E\{I_{1t}\}$	11	–	1	15	–	12	–	11	–	1	14	–	11	–
Closing inventory $E\{I_{2t}\}$	–	1	–	–	3	–	2	–	1	–	–	2	–	1
Expected total cost	2,470							2,430						
Menu 3	$\beta = 0.99$							$\beta = 0.95$						
(Sodium Restricted Diet)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Expected demand	**10**	**12**	**12**	**15**	**13**	**12**	**12**	**10**	**12**	**12**	**15**	**13**	**12**	**12**
Order-up-to-level $E\{R_t\}$	23	–	13	42	–	–	13	35	–	–	29	–	25	–
Closing inventory $E\{I_{1t}\}$	13	–	1	15	–	–	1	25	–	–	14	–	14	–
Closing inventory $E\{I_{2t}\}$	–	1	–	–	16	–	–	–	13	–	–	1	–	2
Closing inventory $E\{I_{3t}\}$	–	–	–	–	–	4	–	–	–	1	–	–	–	–
Expected total cost	943							901						

TABLE 6. Result obtained from an original model with no perishable constraint at $\beta = 0.95$

Menu 2 (Gout)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Expected demand	**10**	**10**	**14**	**12**	**12**	**14**	**10**
Order-up-to-level	25	–	45	–	–	30	–
Closing inventory I_{1t}	15	5	31	19	7	16	6

in period $t = 2$. However, inventory $I_{3t=3}$ will become waste for 6 units since it reached its maximum shelf life period.

Table 6 shows the solution obtained from the original model of Tarim and Kingsman [23]. The perishability constraint is not satisfied since the maximum shelf life is $M = 2$, but the solution obtained is said to be replenished on period $\{1, 3, 6\}$, which will cause an expiration in period $t = 5$ for those raw materials filled in period $t = 3$.

Although the result shown in Table 4 is solved using data from only one case study hospital, all constraints were found to be the same for four hospitals. This paper's real contribution is to propose an approach that has been academically proven to work in a public hospital in a remote area. Any commercial solvers software can solve the MILP used in this paper while desired fill rate ($LevelE\{R_{jt}\}$) can find by any spreadsheet program.

Compared with the current approach of a case hospital, which is simply based on self-experience with no desired fill rate, $E\{R_t\}$ were obtained by making it equal to the sum of max expected demand, as shown in Table 7. The expected total cost was found to be lower, as same as waste from expiration.

Table 7. AS-IS Policy of a case study hospital in Menu 1

Menu 1 (Chronic Kidney Disease)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Expected demand	**15**	**18**	**20**	**20**	**17**	**18**	**17**
Order-up-to-level	60	–	–	60	–	–	20
Closing inventory I_{1t}	45	–	–	40	–	–	10
Closing inventory I_{2t}	–	27	–	–	23	–	–
Closing inventory I_{3t}	–	–	7	–	–	5	–
Expected total cost	3,270						

5. **Discussion and Conclusion.** This paper has explored challenges and constraints in planning therapeutic diet production schedules of public hospitals in remote areas using the case of four Thai hospitals. Firstly, the schedule instability was found neglected when the case study hospitals planned their food production. This result was in the same direction as other studies in other industries: the airline catering industry ([17,41]), the shoe manufacturing industry [40], and automobile industry [41]. The mentioned papers also find that schedule instability was caused by the demand side rather than the supply. Therefore, minimizing schedule instability under irregular demand patterns while planning food production is suggested to be investigated in future.

Secondly, all of the hospitals in this paper are public hospitals located in remote areas. This paper found that scheduling effectiveness received less attention since hospital operations are subsidized by the government, putting planners under less pressure over the cost while planning. This result was also in the same direction as Abderrabi et al. [42], who proposed a mathematical model to improve the scheduling of the hospital food production process through the use of operations research. So one of the potential topics this paper can suggest is optimizing hospital food delivery routes within the building since some hospitals may have to deliver food to more than a thousand beds per meal.

Thirdly, this paper has proposed an MILP for planning the production schedule of the therapeutic diet when dealing with demand uncertainty, especially in Thai public hospitals where demand for meals varies based on daily diagnoses from a medical doctor. The other approach for helping hospitals deal with this kind of demand pattern is to be investigated. For example, Lei [39] applied game theory to implementing resource allocation while optimizing resource scheduling that can minimize system delay and energy consumption.

Lastly, a simulation study to improve kitchen operations is suggested for future research direction since the kitchen of a hospital in a remote area is smaller, with less equipment and staff compared to a regular kitchen.

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