Roadmap for Adopting New Technology in the Utility Industry

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Abstract

In this paper, we develop a framework to optimally manage the time-phased deployment planning of a new technology, namely Advanced Metering Infrastructure, in the Utility industry. Advanced Metering Infrastructure enable two-way communication between residential and commercial customers and the Utility grid, so that energy consumers may respond to price signals during stressful conditions in the grid in a price-sensitive fashion, and reduce the overall stress in the grid. It also enables consumers to shift discretionary energy loads from stressful, peak periods to off-peak periods. We present an end-to-end solution framework for addressing the various analytical challenges that are involved in developing an optimal deployment plan, from a business case development perspective. Our solution framework uses a judicious combination of system dynamics modeling, econometric modeling and mathematical programming based optimization modeling. A system dynamics model is used to estimate the dynamics of user adoption of the new technology, relative to deployment, which results from marketing effectiveness for the new technology, as well as the viral effect of word-of-mouth interactions among users. The model is also used to estimate the lag in benefits realization from the new technology deployment, arising from the above dynamics of user adoption, coupled with a lag in the maturity of the supporting Information Systems that enable effective functioning of the new technology. These estimates are then subsequently used in a mathematical programming model, which solves a multi-period, resource-constrained optimal deployment planning problem that is subjected to the lags in user adoption and benefit realization, which are estimated by the system dynamics model. The mathematical programming model also needs estimates of demand response benefits that are obtainable from effective adoption of the new technology. An econometric model is used to estimate the price-sensitive response of user demand, which is facilitated by the new technology. Lastly, we incorporate a parameter estimation routine that acts as a feedback loop between the output decisions of the planning model, which get implemented, and the system dynamics model. This is so that we may reconcile the parameters in the systems dynamics model, with respect to observations from the market place. Such an end-to-end approach will enable us to use both external market information as well internal financial information and to steer business success.

Keywords: System Dynamics, Market Analysis, Programming Model, Optimization

1. Introduction

Energy Delivery Companies are planning to deploy smart meters for its residential and commercial customers. Such an Advanced Metering Infrastructure (AMI) would enable two-way communication. Specifically, it includes a communication information system and distribution automation system. Companies can use the system to monitor and collect the hourly or sub-hourly electricity usage from each customer and to diagnose occurring problems (trouble shooting). More important, companies can use the system to pose the whole network load and pricing information to customer in real time and expect that price-sensitive customers change their usage pattern to reduce the peak demand and to increase non-peak demand. These features provide the customer feedback mechanisms that encourage economic investment and rational market behavior.

There are several papers that are available to evaluate such a program from demand response perspective [1], [2]. They analyze usage pattern changes for different user groups and different seasons through pilot program in a southern California region. Their models are used to predict the impact of dynamic pricing on demand. Some potential opportunity costs and risks in investing in AMI and related system are identified and investigated.

As mentioned in [1], business cases in support of system-wide AMI implementation has not proven successful, since the scope of issues related to cost-justification of AMI is too narrow and the methodology mainly focuses on minimizing cost. It is a great challenge to predict the profitability from such investment. We face future uncertainty from market demand and resource availability during implementation. Some of benefits, like say, the economic benefits from demand response, depend on customer adoption rate of AMI technology and time-lagged economic effects, which are difficult to estimate due to the dependency on intangible measures, such as marketing effectiveness, word-of-mouth, etc.

In this paper, we address the management issues that are pertinent to implementing an AMI program from a business case development and deployment planning perspective, and propose an integrated end-to-end approach. Firstly, we uses a market diffusion model based on System Dynamics [3],[4] to create a time-varying user adoption profile. It includes marketing effectiveness and word-of-month effect on customer behavior. *The model is also used to estimate the lag in benefits realization from the new technology deployment, arising from the above dynamics of user adoption, coupled with a lag in the maturity of the supporting Information Systems that enable effective functioning of the new technology*. Secondly, we *also need estimates of demand response driven economic benefits that are obtainable from effective adoption of the new technology. An econometric model is used to estimate the price-sensitive response of user demand, which is facilitated by the new technology. Thirdly,* a mathematical programming model is developed to capture the above time-lagged benefits and costs as well as operational constraints for a chosen planning horizon, which is typically order of 15-20 years. By maximizing profit through the model, we achieve an optimized meter deployment plan, across various jurisdictions and over the chosen planning horizon. Lastly, a re-planning step is introduced during the plan implementation process. There are two reasons for introducing this step. One is related to the change of resource and/or budget, which may force re-planning. The other reason is to enable a parameter estimation functionality, which can be invoked to close the plant-model mismatch, in a manner similar to model predictive control in control theory. It allows periodic updating of parameter settings for the market diffusion model based on observed data so far. In other words, the re-planning would close the loop and iteratively calibrate the market diffusion model.

The paper is organized as the following. In section 2, we discuss information flow and program management framework. Section 3 gives formulation detail of the integrated model.

Section 4 demonstrates some simulation results for certain scenarios. Section 5 concludes the paper and discusses further research direction.

2. Program Management Framework

Program Management on AMI implementation is about how to develop and execute a deployment plan. Our proposed solution will address problems for the following two phases: planning phase before implementation and re-engineering during the implementing process.

2.1. Information flow model

Figure 1 shows the information flow among the various modeling components. There are three models in the system (top three boxes). The market diffusion model takes parameters like marketing effectiveness and customer contact rate. These values should be boot-strapped in the first phase and might be obtained from historical data in other technology adoption processes, such as, data from market penetration of natural gas vehicles [6] and observed values from some pilot program of deploying AMI in electricity industry [2]. These values can be calibrated from partially available actual data in the second phase. This model will generate customer adoption rate, as well as the time lag between deployment and benefits realization, as inputs into the optimization model.

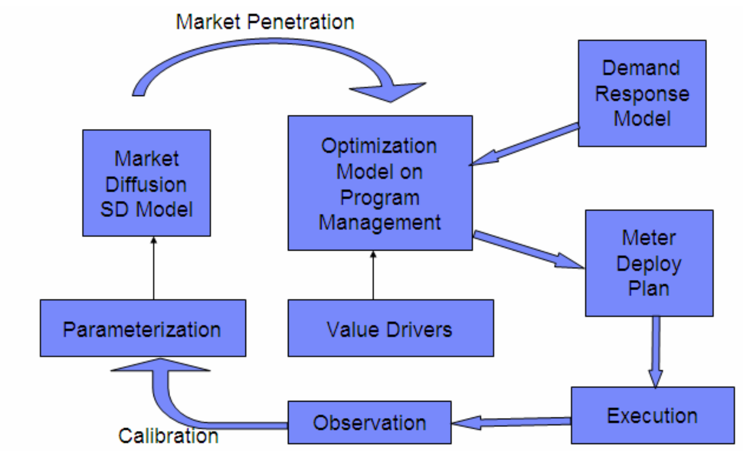

Figure 1: Information flow in proposed framework

The demand response model uses the hourly load and dynamic pricing information, as well pricing elasticity to asses benefit (cost saving) and generate unit benefit (per meter) as a function of penetration rate. The optimization model takes outputs from the other two models as well as value factors, like labor unit cost, material unit cost, etc. and schedule factors, like start date, labor duration (see Figure 2 for detail). This model results in a meter deployment plan that satisfies the specified budget, material supply and workforce constraints. When situation occurs, like cost change, supply shortage and workforce unavailable, during the deployment plan execution, the model can be rerun for the remaining period with new information including the calibrated penetration profile.

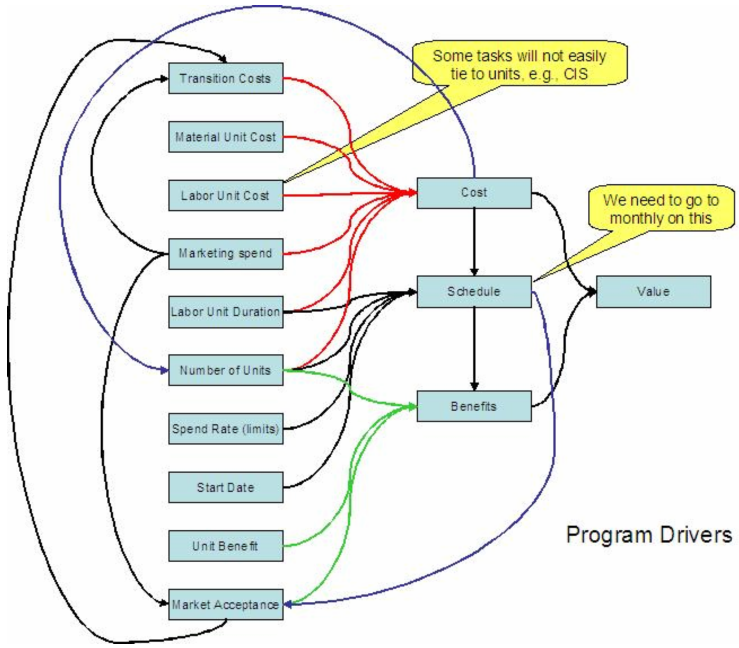

Figure 2: Program Drivers

2.2. Portfolio consideration

There is another issue that we did not address in the last subsection. In fact, the company manages multiple jurisdictions. Due to budget, supply and workforce constraints, it makes sense to deploy smart meter in a certain order among the jurisdictions. There are scenarios in which deploying labor cost are different due to the difference of residential density. Our framework also addresses this issue by allowing user to specify different cost structure and schedule requirements. The optimization model takes all there factors into its formulation and generates an optimal plan that balances the cost and benefit among multiple jurisdictions.

3. Model Formulation

We describe mathematical formulation of three models in this section.

3.1. Market diffusion model

We use the System Dynamics methodology [3, 4] to model market diffusion. System Dynamics gives a capability to visually describe casual relationship among factors (tangible and intangible) and to quantify the relationship in a rational manor (dynamic hypotheses – physical law to drive the system evolution). The model can be calibrated through parameter estimation techniques based on observable data. The market diffusion has been studied and applied to analyze market penetration for other processes of new product and/or technology development, see [5] for case study in new energy technologies and [6] for natural gas vehicles in Switzerland.

In our case, we need to predict customer adoption percentage from time to time among all customers that have smarter meters installed. There are two driving forces to change adoption rate. One is through marketing effort. In fact, after installing smart meter, customers might not be aware of the benefit of that infrastructure and need time to become familiar with the system. The other would be "word of month" effect through customer contact. The following System Dynamics model is shown in the top part of Figure 3 with both influence factors being included.

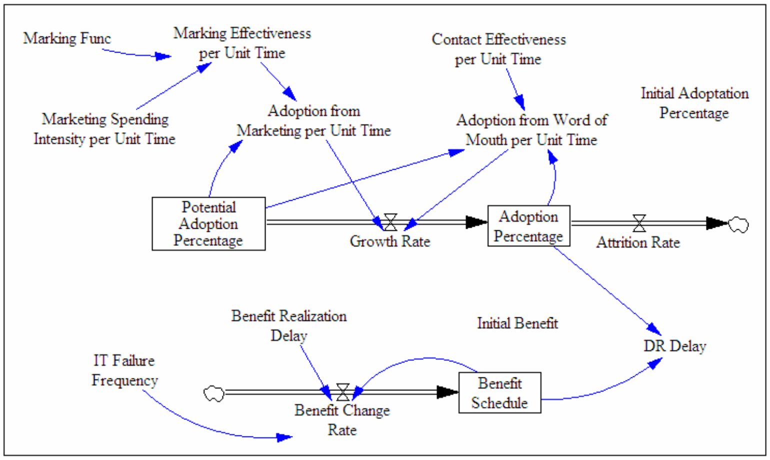

Figure 3: Diffusion & Benefit Realization Model

If write it as a differential equation, we have

$$\frac{dA}{dt} = m \cdot (1 - A) + c \cdot A \cdot (1 - A). \qquad (1)$$

Where A corresponds to "Adoption Percentage" in Figure 3, m is for "Marking Effectiveness per Unit Time", and c is for "Contact Effectiveness per Unit Time". The first term in RHS accounts for the effect from marketing and the second is for the effect resulting from the contact of un-adopted customers with adopted customers. We can solve Equation (1) explicitly and obtain the following solution

$$A(t; m, c, A_0) = \frac{(cA_0 + m) \cdot e^{(c+m)t} - m(1 - A_0)}{(cA_0 + m) \cdot e^{(c+m)t} + c(1 - A_0)}.$$

Its value varies from the initial A_0 to 1 (see Figure 4).

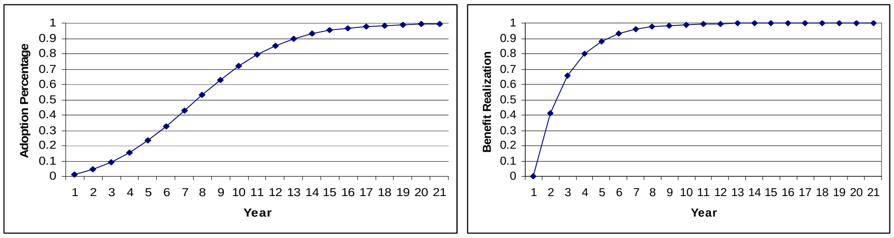

Figure 4: Adoption Percentage and Benefit Realization

Note that, since A is for the adoption percentage, its value is always less than one. In the beginning when the adoption is small (A close to zero), company needs to invest money on marketing and educate customesr to accept and utilize the new technology. The rate increases mainly determined by the first term of Equation (1). As time elapses, the "word of month" influence would become dominant force to convince people to adopt the new technology. The rate increases mainly determined by the second term of Equation (1).

We take A as a multiplier of the number of customers with smart meters installed to figure out the number of adopted customers. The other point we want to make here is that the solution, for the dynamics of customer adoption, applies relative to the point in time when the smart meter is installed. Since the meters can be deployed in different time, current total adopted customers would be the summation of all adopted customers with different installation points in time. Suppose that we use M(s) to represent the number of meters installed at time s. Then the total adopted customer until time t, MA(t), would be equal to

$$MA(t;m,c,A_0)=\sum_{s=0}^{t} M(s)\cdot A(t-s;m,c,A_0)\ .$$

The effectiveness of marketing investment and word-of-month will vary, and these parameters are difficult to estimate accurately to begin with. The contact rate is different for each jurisdiction due to different population density. Sometime, the word-of-month could have negative effect [7]. Some customer groups might not be sensitive to pricing signals and would not be motivated to use the system. Also the initial value for adoption rate depends on marketing condition or technology developing stages (emerging, mature and saturated). The impact from intangible variables related to soft factors, psychological influence is difficult to measure. In order to capture correct adoption rate, we introduce a parameter calibration step in our solution framework. When we are in the process of implementing the AMI deployment, the number of the actual adopted customers is known until current time, say denoted by RA. We can find out proper $\left(m^*, c^*, A_0^*\right)$ by using regression with the least squared error,

$$\left(m^*, c^*, A_0^*\right)=\arg\min\left\{\sum_{\tau=1}^{t}\left[MA(\tau;m,c,A_0)-RA(\tau)\right]^2\right\}.$$

In the case when no real data is available, we can use data from other new technology adoption process to bootstrap the process.

Similarly, we use the first order delay to model benefit realization. The corresponding equation can be written as

$$\frac{dB}{dt}=\frac{\left((1-\alpha)-B\right)}{\tau_D}, \qquad (2)$$

where B is for Benefit realization, α is the smart meter IT failure rate and τ_D is time delay parameter for delay in maturity of information systems. The equation (2) has the following solution

$$B(t;\alpha,\tau_D,B_0)=(1-\alpha)-\left(1-\alpha-B_0\right)\cdot e^{-\tau_D\cdot t},$$

where B_0 is the initial value for B. The behavior of the solution is shown in the second of Figure 4. The solution will asymptotically close to $(1-\alpha)$ for $0<B_0<1-\alpha$. The function is a multiplier and is applied relative to the deployment time of meter, similar to the adoption multiplier A. The $\left(\alpha,\tau_D,B_0\right)$ can be calibrated based on observable data in the same manner for A.

3.2. Demand response model

The approach followed here is based closed on the RAND report [8]. Assume that the customer with an installed smart meter will receive real time electricity prices and is price sensitive. The focus here is to estimate the cost saving associated with demand shifting from peak periods to off-peak periods (see Figure 5 for illustration).

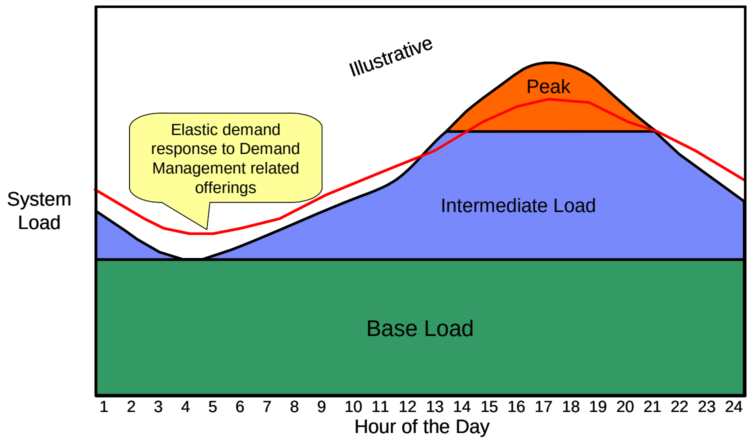

Figure 5: The electricity demand profile for a typical day

In order to assess the cost savings related to demand shaping from market, we need to estimate the following quantities:

- Market penetration (M_p). Percentage of customers that have smart meter installed would take advantage of this feature and change their energy usage pattern. In fact, this is the same as the adoption percentage discussed in the last subsection.
- Price elasticity of demand (η). Percentage change in the demand for a 1% change in price. We have estimated this using an empirically determined coefficient for price elasticity of demand [9]. Typically price sensitivity is negative (demand reduce with price increases). We have chosen a nominal value of -0.1 with a spread of [-0.15, -0.05].
- The supply curve is approximated by using the hourly price and load for each day. This data can be plotted as a curve from demand to clearing price (we need to sort the price-demand pairs in ascending order of price). For any given price, the load can be determined by interpolating over this curve.

Demand shaving L_c is determined by the following

$$L_c = \eta \cdot \frac{(p - p_b)}{p_b} \cdot (L - L_b) \cdot M_p ,$$

where L load, L_b base load, p price, p_b the fixed price. The second factor on the RHS is the percentage change of price. The price p_u corresponding to the update load $L + L_c$ is interpolated for the price within the supply curve that is approximated using hourly loads and clearing prices. Note that we smooth out the variability in the data locally (using a 3-4 hour time window). The saving is given by

$$(L - L_p) \cdot p - (L + L_c - L_p) \cdot p_u .$$

That value is positive for $p > p_b$ (increase price during peak hour) since $L_c < 0$ and $p_u < p$. Note that, the savings for even low penetration (20%) of smart meters is substantial. However, many of the inputs, like fixed price, price elasticity are based on guesstimates and hence need further calibration. This can also be accommodated through some Monte Carlo based uncertainty analysis.

3.3. Optimization model

Mathematical programming techniques have been used to address the time-tabling problem, to generate manufacturing plan and schedule to meet demand. We use the technique to create smart meter deployment plan in the next 20 year horizon. The output from the models described in the last two subsections is used in our benefit estimates during the process of deploying smart meters. We only include benefit and cost related deploy schedule.

Our objective is to find a deployment plan such that it maximizes benefit and minimizes cost. Suppose that the variable for deployment plan is written as $Y[j,t]$, subscript j is for the jurisdiction index, and t is for time period. Formally, the objective can be expressed as

$$(O): \quad \max_{Y}\left\{\sum_{j=1}^{N}\sum_{t=1}^{T}\left(Benefit - DeployCost - OMCost - ExtraWF - h * ExtraM\right)[j,t]\right\}.$$

Where h is for holding cost of extra meter in hand, N is the number of jurisdictions and T is the time horizon. The expression sums over jurisdictions and over multiple time periods. Its solution would address both the portfolio concern as well budget distribution among time horizon. The last two terms are used to penalize the extra meter supply and extra workforce. In fact, without them, the solution tends to allocate the enough resources at the first period.

The value of $Y[j,t]$ varies from 0 to 1, and represents the percentage of meters that get installed, relative to the number of customers. Under the constraint of early start $ES[j]$ and late finish $LF[j]$, we have the following constraint, for each jurisdiction j

$$(C1): \quad \sum_{t=1}^{T} Y[j,t] = 1; \quad Y[j,t] = 0 \ \text{ for } t \notin \left[ES[j], LF[j]\right].$$

3.3.1. Benefit formulation

Note that benefits are associated with the cumulative number of meters that have been installed, and depend on how long has any individual meter been installed (to account for the lag in the benefit realization profile mentioned in the subsection 3.1). We assume availability of estimates of the unit benefits BU and percentage growth BG related to various benefit categories (customer contact benefit, demand response benefit, meter reading benefit, asset optimization benefit etc.). For instance, meter reading benefit is formulated as

$$mrBenefit[j,t] = BU_{mr}[j] \cdot \left(1 + BG_{mr}[j]\right)^{t-1} \cdot M[j] \cdot \sum_{s=1}^{t}\left\{B_j(t-s)\left(Y[j,s] + GR[j] \cdot \sum_{\tau=1}^{s} Y[j,\tau]\right)\right\},$$

where $M[j]$ denotes the number of current customers who are considered to convert into smart meters. $GR[j]$ is customer growth rate in that jurisdiction j and $B_j(t)$ is benefit realization profile created from system dynamics model. The demand response benefit is slight different from others, since it also related to customer adoption rate $A(t)$ that was estimated in system dynamics model. The unit of benefit BU_{dr} for it is obtained from the demand response model in subsection 3.2.

$$drBenefit[j,t] = BU_{dr}[j] \cdot (1 + BG_{dr}[j])^{t-1} \cdot M[j] \cdot \sum_{s=1}^{t} \left\{ A(t-s) \cdot B_j(t-s) \left(Y[j,s] + GR[j] \cdot \sum_{\tau=1}^{s} Y[j,\tau] \right) \right\}.$$

3.3.2. Deployment and operation maintenance cost

Deployment cost is associated with activities to install/or replace the meter. It includes both equipment cost and labor cost. There is difference between the initial deployment cost and later replacement cost, since the latter only includes the incremental portion. We also include the inflation associated to labor and equipment into cost structure. For simplicity, cost difference related to types of customer is ignored in the description of formulation. Mathematically, the deploy cost is written as, for jurisdiction *j* at the time *t*,

$$DeployCost[j,t] = \left[C_{md}[j] \cdot (1 + I_{eq})^{t-1} + C_{ld}[j] \cdot (1 + I_{la})^{t-1} \right] \cdot M[j] \cdot Y[j,t] + \left[C_{mr}[j] \cdot (1 + I_{eq})^{t-1} + C_{lr}[j] \cdot (1 + I_{la})^{t-1} \right] \cdot M[j] \cdot (GR[j] + NR[j]) \cdot \sum_{s=1}^{t} Y[j,s].$$

Where the parameters used in the formulation are listed here

C_{md} : The equipment cost for deployment, per meter

C_{ld} : The labor cost for deployment, per meter

C_{mr} : The equipment cost for replacement, per meter

C_{lr} : The labor cost for replacement, per meter

C_{om} : The communication cost during operation, per meter

C_{ls} : The labor cost for service, per meter

I_{ep} : The inflation rate for equipment, per year

I_{la} : The inflation rate for labor, per year

NR : The normal replacement rate, per year

Note that first term is for deployment cost and the second term is for growth and normal replacement cost. Similarly, operation maintenance cost is given as

$$OMCost[j,t] = \left[C_{om}[j] \cdot (1 + I_{eq})^{t-1} + C_{ls}[j] \cdot (1 + I_{la})^{t-1} \right] \cdot M[j] \cdot \sum_{s=1}^{t} \left\{ Y[j,s] + GR[j] \cdot \sum_{\tau=1}^{s} Y[j,\tau] \right\}.$$

The difference with deployment cost results from that of the maintenance cost is associated with the total number of meters being installed over time from 1 to *t*.

3.3.2. Penalty related to resources

If we include additional variables for hiring, releasing workers and meter acquisition in our formulation, then we can address issues associated to supply delay and workforce shortage. Note that both deployment and operation maintenance includes the labor cost that is formulated based on the unit cost per meter. If we assume average cost per worker C_w , then this cost can be translated into deploy and service workforce capacity requirement.

$$deployWC[j,t] = C_{ld}[j]\cdot(1+I_{la})^{t-1}\cdot M[j]\cdot Y[j,t]$$
$$+ C_{lr}[j]\cdot(1+I_{la})^{t-1}\cdot M[j]\cdot(GR[j]+NR[j])\cdot\sum_{s=1}^{t} Y[j,s]/C_w$$
$$serviceWC[j,t] = C_{ls}[j]\cdot(1+I_{la})^{t-1}\cdot M[j]\cdot\sum_{s=1}^{t}\left\{Y[j,s]+GR[j]\cdot\sum_{\tau=1}^{s}Y[j,\tau]\right\}/C_w.$$

The available workforce capacity can be written as

$$availableWC[j,t] = W_i[j] + \sum_{s=1}^{t}\left(W_h[j,s-LT_h]\cdot EL[t-s-LT_h+1] - W_r[j,s]\right)$$
$$(C2):\quad \sum_{s=1}^{t}\left(W_h[j,s-RT] - W_r[j,s]\right)\geq 0$$
$$(C3):\quad availableWC[j,t]\geq deployWC[j,t]+serviceWC[j,t].$$

Where W_i is the number of initial workers, $W_h[\cdot,t]$ is the number of acquired workers at time *t*, $W_r[\cdot,t]$ is the number of released workers at time *t*. The parameter $EL[t]$ is an experience level multiplier and changes from some value less then 1 to 1. The new hired workers need time to learn and catch up, and then become fully experienced. The parameter *RT* in (C2) is minimal residence time for a new hired worker before which, the worker may not be released. The constraint (C2) specifies the relationship between hiring and releasing workers. The constraint (C3) means that we need enough workers to carry out tasks. Note that *deployWC, serviceWC* are just intermediate variables.

Now we formulate *ExtraWF*, that is extra cost associated with hiring and learning activity, sitting on bench (less utilized) due to worker release delay (minimal residence). It is given by

$$ExtraWF[j,t] = C_w\cdot(1+I_w)^{t-1}\left\{LT_h\cdot W_h[j,t]\right.$$
$$\left.+\sum_{s=1}^{t}\left(W_h[j,s-LT_h]-W_r[j,s]\right) - deployWC[j,t] - sevicesWC[j,t]\right\}.$$

Without the term in the objective function, we could get a solution to hire enough workers in the first period and to release nobody in the later periods.

Let $MP[\cdot,t]$ be procuring meters at time *t*. The *ExtraM* is equal to the accumulated number of procured meters minus the accumulated number of required meters

$$ExtraM[j,t] = MI[j] + \sum_{s=1}^{t} MP[j,t-LT_m]$$
$$- M[j]\cdot\sum_{s=1}^{t}\left\{Y[j,s]+(GR[j]+NR[j])\cdot\sum_{\tau=1}^{s}Y[j,\tau]\right\}.$$
$$(C4):\quad ExtraM[j,t]\geq 0$$

Where *MI* are initial available meters, LT_m is procuring lead time. So the first two terms represent available cumulative number of meters at time t. The third term, the accumulated number of required meters, includes deployment, growth and normal replacement portions. Without the term (*ExtraM*) in objective function, we could get a solution to procure all meters in the first period.

3.3.2. Constraints being considered

There are several resource constraints that can be imposed when we solve the optimization problem, like budget upper bound, available workforce upper bound, procuring meter upper bound as well as benefit lower bound (least benefit expectation). Mathematically, at time t,

$$(C5):\quad \sum_{j=1}^{N}\left(DeployCost[j,t]+OMCost[j,t]+ExtraWF[j,t]\right)\le investUB[t],$$

$$(C6):\quad \sum_{j=1}^{N}W_h[j,t]\le hireUB[t],$$

$$(C7):\quad \sum_{j=1}^{N}MP[j,t]\le procureUB[t],$$

$$(C8):\quad \sum_{j=1}^{N}Benefit[j,t]\ge benefitLB[t].$$

By imposing some combination of constraints (C5) to (C8), we can address different concern or issues during the deploy process. We demonstrate some cases in the next section.

4. Simulation Scenarios and Results

In the case of excluding *ExtraWF* and *ExtraM* in the objective function, we would get a trivial solution from minimizing the objective without any constraints. The best solution is to hire all needed workforce in the first period and to procure all needed meters in the first period since it does not involve any cost in the objective function, and to deploy all meters in the earliest start period, since it would achieve the maximum benefit. By including *ExtraWF* and *ExtraM* in the objective function, even without any constraints, the answer would be different: a) hiring would spread among whole evaluation horizon with periodic releases (aligned with the optimal deployment plan) due to hiring cost and on-bench wasted cost, b) procurement of meters would be based on requirement that aligns with the deployment plan, c) the deployment plan wpuld potentially spread across multiple periods between the specified earliest start and the latest finish periods. From the optimized solution, we can obtain the benefit, cost, workforce hiring, and meter procurement profile along considered timeline.

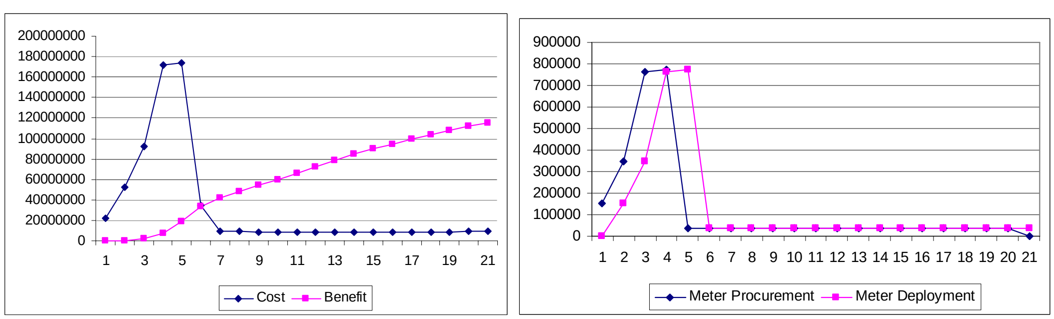

Figure 3: Cost and Benefit during 21 year periods

Figure 3 shows the cost and benefit as well as the corresponding meter procurement for a time horizon of 21 years. Cost has a peak during deployment years (from 2 to 6) and benefit will pick up gradually after meters being installed. The meter procurement (the right) has the same figure as the meter deployment except it shifts to the left by one period due to procuring lead time. Figure 4 shows the corresponding workforce profile. The span of peak is much wider due to hiring and training lead time (time taken to become fully experienced), and the minimum residence time constraint (worker can not be released immediately after hiring). The shape can be different in the outsourcing case in which, an outsourced worker can be released right away after finishing deployment. The right figure shows cash flows for two cases: one with demand response benefit and the other one without it. The investment for deploying smart meters will payoff around year 14. The utility company will achieve profit based on that schedule.

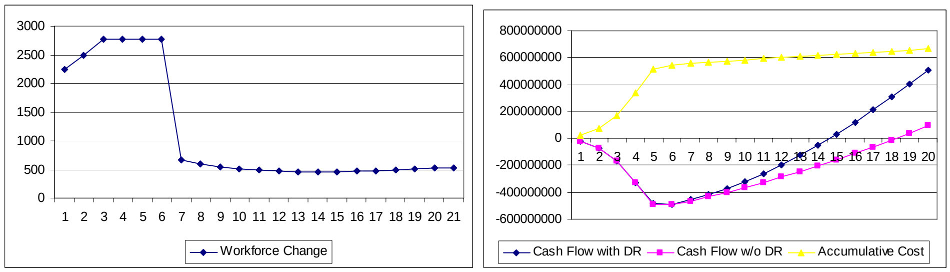

Figure 4: Workforce Change and Cash flow

Figure 5 shows the accumulative percentage deployment plan in different jurisdictions. For specified earliest start and latest finish periods, the optimizer would create the deployment plan in term of percentage of total current customers in that jurisdiction. Note that the solution gives even distribution among the specified deployment periods under no budget constraints. The solution would be different for mixed integer programming formulation, in which, we allow users to specify, the early start, late start, duration and late finish, and we can get a solution with different deploy cover periods.

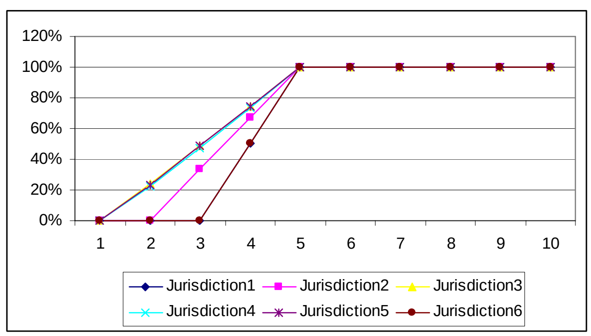

Figure 5: Accumulative percentage deployment among jurisdictions

From Figure 3, we know that the cost at deployment peak could be very high. It is reasonable to impose annual budge and/or procurement constraints, and to relax late finish requirement. Figure 6 shows the cost, benefit and deploy plan under budget limit to be $100M during deploy period. Figure 7 shows the cost, benefit and procurement profile under both budget limits to be 100M and meter procurement limit 380,000.

The model also allows user to specify predefine deploy plan (specify percentage of meters deployed in each year for each jurisdiction). Then the optimizer would create cost, benefit, workforce and meter procurement profile. User can further add meaningful constraints based the above outputs and re-create new deploy plan. In the case of deployment being the half way of process, the model can be used to re-plan based on observable data. User can specify deploy percentage happened in the past and use the optimizer to create deploy plan for the rest of periods.

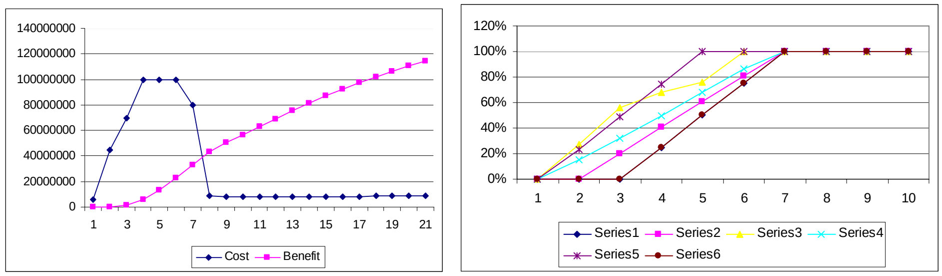

Figure 6: Cost, Benefit and Deploy Plan under Budget Constraint

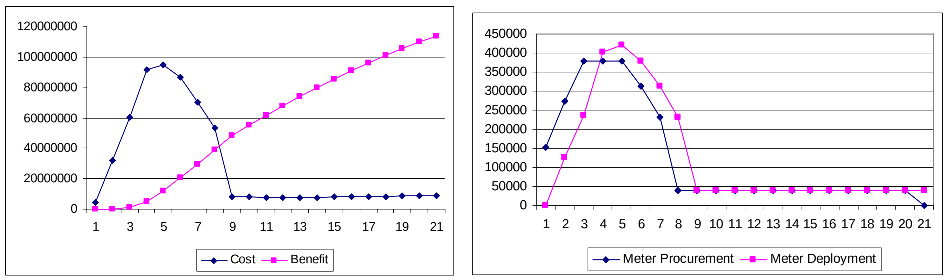

Figure 7: Cost, Benefit and Procurement under Budget and Supply Constraints

5. Conclusion

We propose an integrated model for AMI program management. It takes advantage of both system dynamics and linear programming methodologies. System dynamics is used to estimate intangible measure in the AMI deploying program management, like market penetration and benefit delay and employee experience profile. The linear programming is used to create deploying plan, meter procurement and workforce requirement. The model can address operation issue related to budget constraint, workforce and supply shortage. The feedback loop is built into the system in a general sense that the parameters in system dynamics can be calibrated from observable data as the program progresses.

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